MEASURING COGNITIVE ENGAGEMENT AND

MOTIVATION IN INFORMAL CONTEXTS

by

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A dissertation submitted in partial fulfillment
of the requirements for the degree

of

Doctor of Philosophy

in

Education

MONTANA STATE UNIVERSITY
Bozeman, Montana

April 2018

# DEDICATION

First, this dissertation is dedicated to my great love and husband, John. What a long, strange trip it's been. Also written in memory of my grandfather, Leonard John, who would have loved to be here to witness this process.

I must also dedicate the study to the powerful minds that have surrounded and guided my life. If you meet my mother, you will understand what I mean. My family is strong and full of light. If you meet my father, you will understand what I mean. No matter how far my brothers are, I am inspired by their passion and perseverance. Thanks for the love.

## ACKNOWLEDGEMENTS

This research is based upon work supported by the National Science Foundation (NSF) Advancing Informal STEM Learning Program under Grant No. 1423561 and the National Aeronautics and Space Administration (NASA) under Grant No. NNX16AB86A. Any opinions, findings, and conclusions or recommendations expressed are those of the authors and do not necessarily reflect the views of NASA or the NSF.

First, acknowledging the work and support of principle investigators on the grants, Dr. Anthony Hartshorn, Dr. Nicholas Lux, and Dr. Jamie Cornish seems insufficient. They were directly involved in the process, supporting and challenging me at every step. It’s as much their accomplishment as it is mine. Thank you for trusting me.

Second, thank you to Dr. Michael Brody for sticking with me. I appreciate your patience and guidance. You’ve influenced how I see teaching and research. I couldn’t have asked for a better mentor. Also, thank you to Dr. Carrie Myers and Dr. Arthur Bangert for being there to challenge me and to foster my development as a scholar.

Next, three cheers to those in middle earth. You all have left an indelible mark on my life and influenced my ways of thinking and being. Thanks to Spencer Johnson and Lincoln Davie for bringing humor to all that you do. Thanks to Brett Tallman, I have enjoyed being challenged by you. To Kayte Kaminski, Catherine Johnson, and Rose Vallor, thank you for your endless positivity, encouragement, and support. I look forward to saying, “I knew you all, when!”

Finally, thank you to Altitude Athletics and the community that has cheered me on throughout the process. You are all a source of constant inspiration.

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# ABSTRACT

Middle school (G5-8) students' cognitive engagement, motivation, and future aspirations in science were quantified within informal contexts (week-long summer camps) with self-reported measures of cognitive strategies, self-regulation, value, self-efficacy, and future aspirations over the course of two phases (N = 152, N =140). The participating middle school students engaged in one of two informal science summer camp opportunities. Informal science experiences may be places which participants can gain science-related capital in equitable ways. This study set out to test the growth in cognitive engagement, motivation, and future aspirations in science differed from students of varying genders, races, and socioeconomic statuses. Survey results over the course of two phases were analyzed via partial-least squares structural equation modeling to explore whether cognitive engagement and motivation predicted future aspirations in science, such as taking high school courses or pursuing a career in the sciences. As operationalized, cognitive engagement (cognitive strategies and self-regulation) and motivational (value and self-efficacy) constructs significantly predicted future aspirations in science ($R^2 = 0.29$, $p < 0.05$). Growth in cognitive engagement and motivation were also investigated to understand if students of different genders, races, and socioeconomic statuses have different experiences, with only small differences being uncovered. Results support the claim about the key role that cognitive engagement, motivation, and informal learning experiences may play to encourage future aspirations in science and show the ability of these experiences to foster the development of these skills in equitable ways. Better understanding cognitive engagement and motivation and how these are influenced by informal science experiences could improve the effectiveness of these interventions to foster students' future aspirations in science, a continuing societal priority, in ways that do not fall into the same patterns of inequality that seem to persist in formal education.

# CHAPTER ONE: INTRODUCTION

Developing a strong science, technology, engineering, and math (STEM) workforce continues to be a pressing need for the United States (National Research Council, 2011; National Academies of Sciences, 2016), since STEM capabilities significantly impact the United States' ability to be innovative and rise to the challenges the future will bring (Nation Science Board, 2015; President's Council of Advisors on Science and Technology, 2010). In addition, the knowledge and skills learned in STEM education will enable people to continue to be informed and capable in an increasingly complex society (Archer, Dawson, Dewitt, Seakins, & Wong, 2015). Yet, evidence unfortunately suggests a potential decline in student motivation to engage with STEM around the transition to middle school (Vedder-Weiss & Fortus, 2011, 2012). Furthermore, achievement and interest in STEM appear to suffer from persistent gender and racial/ethnic inequities (Riegle-Crumb, Moore, & Ramos-Wada, 2011; Sadler, Sonnert, Hazari, & Tai, 2012). These inverse trends argue for alternative or unconventional strategies or approaches to improve STEM learning experiences for all participants (Cannady, Greenwald, & Harris, 2014).

While benchmarks like high school coursework and school achievement (Sadler, Sonnert, Hazari, & Tai, 2014; Wang, 2013) continue to be important predictors of future STEM involvement, "attention on benchmark completion…diminishes attention to the motivation for completing the benchmark" (Cannady et al., 2014, p. 447). How students perceive learning experiences depends on their interest (Tai, Liu, Maltese, & Fan, 2006), motivation, and engagement (Pintrich & De Groot, 1990; Sinatra, Heddy, & Lombardi, 2015). Informal contexts might be just one way to encourage this critical STEM engagement.

Defining informal education can be seen as anything “non-school” (National Research Council, 2009, p. 28), or “out-of-school-time” (NSTA, 2012, p. para. 1), or as more of an approach to education that focuses on the voluntary and learner-driven nature of the experience (Wellington, 1990). Learning that occurs in these spaces (Falk & Storksdieck, 2005), the structure of programs, or the approach the teacher takes to the experience (Eshach, 2007) can also define informal education. For this study, informal experiences will follow the characterization set by the National Research Council (2009) and will discuss informal experiences as those taking place outside of the traditional school setting, in spaces such as museums, after-school programs, parks, and summer camps.

As stressed by the National Research Council (2009), informal environments represent a natural context for studying STEM learning, STEM career orientation (Nugent et al., 2015), and STEM interest most broadly (Dabney et al., 2012). Thus, informal contexts hold great potential for fostering learner engagement and improving learner motivation in STEM, but as with any educational program (formal and informal), it is essential that these programs quantify the extent to which program offerings increase learner outcomes, a research arena that remains largely unexplored (Martin, Durksen, Williamson, Kiss, & Ginns, 2016).

Research on engagement has been called for (Sinatra et al., 2015) due to its positive links with student achievement (Greene, 2015) and motivation, including future aspirations in science (Martin et al., 2016). Though the bounds of this metaconstruct is debated, the framework put forth by Fredricks, Blumenfeld, and Paris (2004) which describes engagement as encompassing affective, behavioral and cognitive domains, is widely used. Given engagements multifaceted nature,

> it has the potential to link areas of research about antecedents and consequences of how students behave, how they feel, and how they think. Ultimately…, it can result in commitment or investment and thus may be a key to diminishing student apathy and enhancing learning (Fredricks et al., 2004, p. 82).

Engaging students in science education is particularly provoking as it conjures notions of students who are not only going through the process of being a scientist (behavioral engagement) but also connecting emotionally with the material (affective engagement) and using complex strategies to understand and adapt to the challenges associated with scientific investigation (cognitive engagement).

Engagement, like one of its antecedents, motivation, is contextually linked and can change over time and place (Christenson, Reschly, & Wylie, 2012). This is an important distinction as it allows interventions and/or changes to individuals context or circumstance to alter overall engagement and motivational levels (Finn & Zimmer, 2012, p. 105).

## Theoretical Framework

### Engagement

Engagement was originally conceptualized within school contexts to describe the collective factors that lead K-12 students either to complete or drop out of school

(Mosher & MacGowan, 1985), and encompassed factors such as skills, attitudes, and behaviors. However, engagements influence extends beyond K-12 education, impacting post-secondary education choices (Carini, Kuh, & Klein, 2006; Kuh, 2003, 2009), academic success (Marks, 2000), and life aspirations (Tytler et al., 2008, p. viii). Engagement is a far-reaching metaconstruct that encompasses a number of literature bases, theoretical frameworks, and many disciplinary boundaries. There remain issues with its operationalization and measurement. Noted by Reschly and Christenson (2012) and Azevedo (2015), several prominent frameworks exist that delineate engagement in different, and unfortunately, sometimes contradictory categories. Given this lack of conceptual clarity, clearer definitions of engagement are necessary (Christenson, Reschly, & Wylie, 2012, p. vi). Following Fredricks, Blumenfeld, and Paris (2004), this study defines engagement as a multidimensional concept encompassing behavioral, affective, and cognitive domains.

This study explores the nexus between cognitive engagement and motivation given the need in the literature to differentiate between these constructs (e.g. Sinatra et al., 2015) as well as their wide-reaching positive impacts in student's success in education (e.g. Greene, 2015; Guo, Marsh, Parker, Morin, & Dicke, 2017; Guo, Parker, Marsh, & Morin, 2015). Further, particular to informal contexts, cognitive engagement may be the most useful dimension of engagement to explore as both affective and behavioral domains may be less important given the fluid and voluntary nature of learning.

Cognitive Engagement. In order to operationalize cognitive engagement, this study measures self-regulation skills and the use of cognitive strategies. Eilam & Reiter (2014) argue that self-regulation skills are essential to effectively learn science given current educational goals. Being able to self-monitor and set goals are hallmarks of self-regulated learning (Pintrich & De Groot, 1990) and may encourage the use of diverse cognitive strategies. Cognitive strategy use, as highlighted by Greene (2015), is often viewed along a shallow and deep or elaborative dichotomy with deep strategy use being associated with performance. However, when exploring cognitive strategy use in STEM domains, the relationship between performance and deep/shallow cognitive strategies show "greater complexity" (Greene, 2015, p. 15) than expected.

Motivation. Regardless of the cognitive strategies known and used by a student, they must first be motivated in order to use these abilities (Blumenfeld, Kempler, & Krajcik, 2006; Pintrich & De Groot, 1990). Though there continues to be a debate concerning the difference between engagement and motivation (Christenson et al., 2012), motivation is "often present implicitly or explicitly in most characterizations of engagement" (Sinatra et al., 2015, p. 2). Intriguingly, the differentiation of these concepts may be inconsequential, and some researchers have chosen to combine and discuss them as a single unit of engagement and motivation (Martin, 2008).

For the purposes of this study, motivation has been operationalized based the expectancy-value theory (Wigfield & Eccles, 2000), which centers on the expectations for success held by students, often viewed as self-efficacy (Bandura, 1997; Pintrich & De Groot, 1990), and the degree to which they value the task given a cost (Blumenfeld et al., 2006; Hulleman & Harackiewicz, 2009; Wigfield & Eccles, 2000). In other words, motivation can be viewed as the intersection between ability beliefs, expectancy, and value, with both ability beliefs and expectancy being related to an individual's view of how well they can do in a task either currently or in the future (Aschbacher, Ing, & Tsai, 2014). Further, this study measures motivation in science specifically, as motivation in one content domain does not necessarily equate motivation in another (Wigfield & et al., 1991), thus clarifying the domain and context are necessary to encouraging construct validity.

## Problem Statement

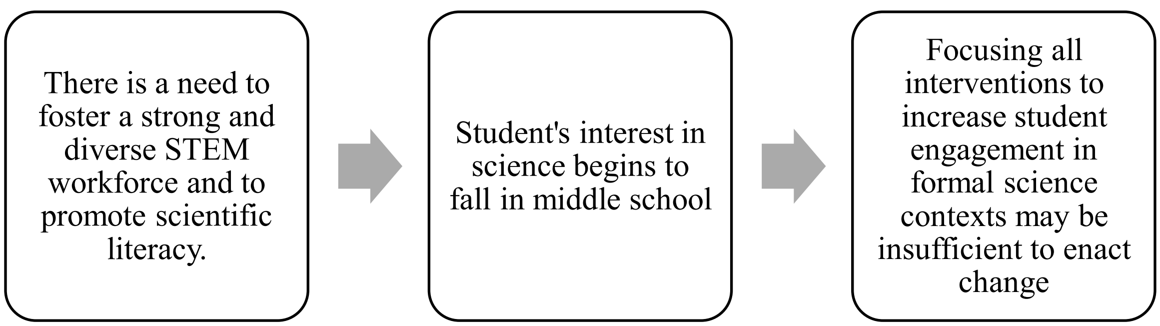


Figure 1. Problem statement

The notion of student engagement becomes exceptionally important in science given the evidence that suggests "science is failing to engage young people" (Archer et al., 2012, p. 882) coupled with the declining interest in science from elementary to middle school (Tröbst, Kleickmann, Lange-Schubert, Rothkopf, & Möller, 2016). The milestone findings of Tai, Liu, Maltese, and Fan (2006) show that by the end of middle school, students interest in science is already formed and that students who expected to pursue a science-based career at this time were 3.4 times more likely to persist in these aspirations in higher education.

Additionally, creating a growing workforce with science, technology, engineering, and math (STEM) knowledge and skills continues to be linked with the overall future development of the United States (National Researc Council, 2011; National Academies of Sciences, 2016; President's Council of Advisors on Science and Technology, 2010; Sinatra et al., 2015). Taken altogether, these findings seem to create a "tipping point" or short window within which to influence student's interest and future aspirations in science.

Sadly, despite the promise of student engagement in relation to positive academic outcomes and the potential "tipping point" in student's desire to pursue science, research on engagement struggles with issues of conceptual clarity (Reschly & Christenson, 2012; Sinatra et al., 2015). As engagement is a multifaceted construct, it crosses into existing literature bases such as research on motivation making differentiation difficult. Further, because of its inherent meta-nature, instruments that get at both the interconnections between the affective, behavioral, and cognitive domains while still maintaining context specificity is difficult and may not get at the "grain size," or level of specificity, needed to answer specific questions related to science (Sinatra et al., 2015).

Lastly, the study of engagement has largely been restricted to formal learning contexts as the history of the term is rooted in school dropout rates. As such, much of the literature fails to capitalize on the promise of informal learning contexts (Falk, Storksdieck, & Dierking, 2007; Martin et al., 2016). Informal learning contexts (such as museums, forests, after-school programs, homes, and nature centers) provide a unique opportunity to investigate learner engagement as learning in these contexts is often directed by the learner, driven by interest, and voluntary in nature (National Research Council, 2009; Wellington, 1990). Further, the majority of a person's life is spent outside of the classroom, even factoring out time for sleep (Stevens, Bransford, & Stevens, 2005).Therefore understanding how people engage in and with these contexts is essential towards realizing the potential influence that engagement has on an individual's learning The expansion of education to encompass informal experiences is critical when trying to envision a holistic approach to learning, one that includes "life-long, life-wide, and life-deep" outcomes. Education should encompass the learning needed for everyday life, for personal growth, and for moral and ethical action, which occurs beyond the bounds of formal education settings (Banks et al., 2007, p. 12).

## Purpose Statement

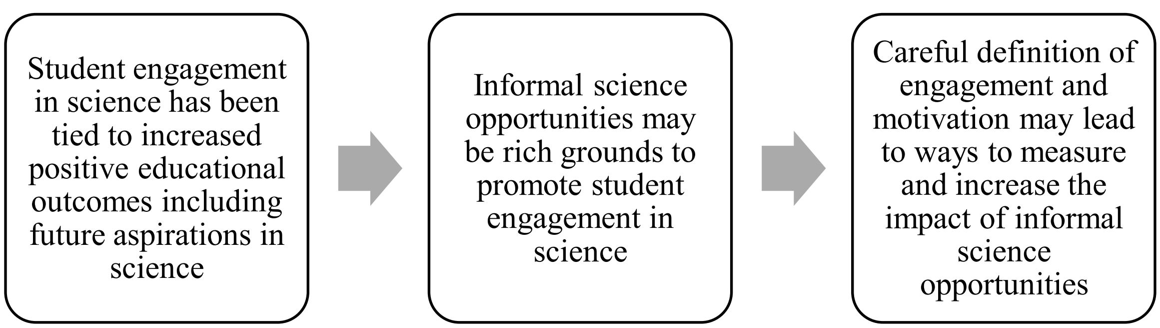


Figure 2. Purpose statement

Currently, there exists a gap in the body of empirical research on cognitive engagement and motivation specific to informal STEM contexts. Given the role that cognitive engagement and motivation might play in encouraging learners to pursue STEM fields in the future, it is essential that we assess these factors in informal contexts. An assessment of this sort could provide informal STEM educators a critical diagnostic tool for understanding the degree to which an educational intervention is influencing learners' cognitive engagement, motivation, and future STEM aspirations. Therefore, an overarching purpose of this study is to measure cognitive engagement (self-regulation and cognitive strategies) and motivation (self-efficacy and value) in an informal setting.

Based on a review of the literature, Figure 1 shows the proposed relationships between cognitive engagement (cognitive strategies and self-regulation), motivation (value and self-efficacy), and future aspirations in science. Both motivational and cognitive engagement constructs have been shown to predict future aspirations in science (Martin et al., 2016; Sinatra et al., 2015). However, the motivational constructs (value and self-efficacy) are theorized to be the antecedents or intent behind engagement, therefore the two constructs measuring motivation are predictors of engagement constructs (Martin, 2012; Reschly & Christenson, 2012). Like Pintrich & DeGroot (1990), self-efficacy is proposed to positively influence engagement (cognitive strategies and self-regulation) but does not directly predict measures of future aspirations in science. Value, which contains measures of interest and of perceived relevance or benefits of the tasks, directly predicts future aspirations in science (Tai et al., 2006), but also will foster learners use of cognitive strategies and self-regulation skills (Blumenfeld et al., 2006; Greene, Miller, Crowson, Duke, & Akey, 2004). Finally, cognitive strategies and self-regulation are posited to predict future science achievement (Greene et al., 2004), which is a common indicator in future aspirations in science (Sadler et al., 2012, 2014; Wang, 2013).

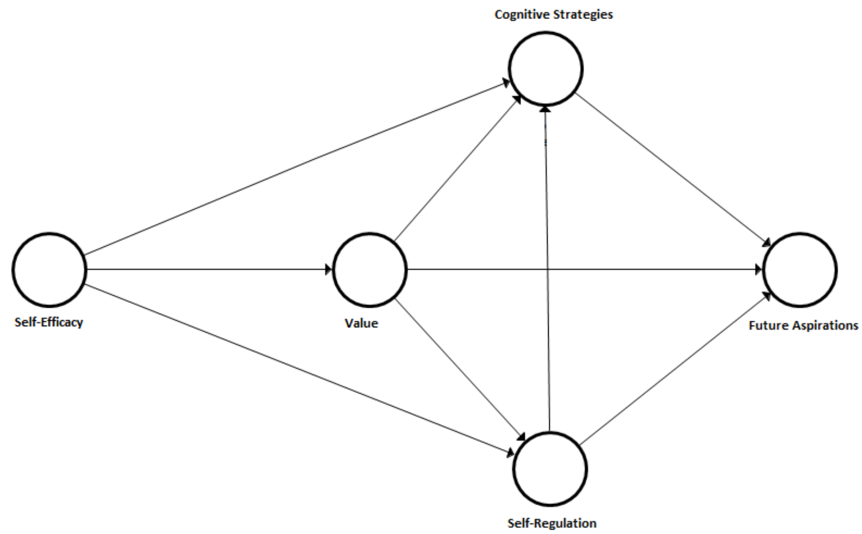


Figure 3 Proposed relationships between self-efficacy, value, cognitive strategies, and self-regulation

## Guiding Research Questions

This study represents two distinct research phases aimed at understanding middle school learner's cognitive engagement and motivation in science and how these are impacted by informal science opportunities. The first phase of this study (Phase One) covers the development of a new survey tool and the associated initial reliability and validity (criteria outlined in Chapter Three) of the instrument. Phase Two expands on the first by updating the survey tool, and by exploring if cognitive engagement, motivation, and future aspirations in science are influenced by a learners' demographic intersections including race, gender, and socioeconomic status.

Phase One:

1) To develop a tool by which to measure cognitive engagement and motivation in science specific to informal contexts; What survey questions operationalize cognitive engagement and motivation in science specific to informal contexts for middle school learners?
2) To measure the impact of informal science experiences on future aspirations in science; What impact does informal science experiences have on middle school learner's future aspirations in science?

Phase Two:

1) To measure the impact of informal science experiences on future aspirations in science; What impact does informal science experiences have on middle school learner's future aspirations in science?
2) To understand how demographic variables (gender, race, socioeconomic indicators) influence or impact growth in cognitive engagement, motivation, and future aspiration in science in informal contexts;
    i) As a result of an informal science experience, what is the relationship between middle school learner's cognitive engagement and their gender, race, and socioeconomic statuses?
    ii) As a result of an informal science experience, what is the relationship between middle school learner's value of science and their gender, race, and socioeconomic statuses?

iii) As a result of an informal science experience, what is the relationship between middle school learner's self-efficacy in science and their gender, race, and socioeconomic statuses?

iv) As a result of an informal science experience, what is the relationship between middle school learner's future aspirations in science and their gender, race, and socioeconomic statuses?

## Limitations and Delimitations

Both of the phases included in this study are quantitative in nature. As such, the stories that they can tell are limited in that they do not provide thick and rich descriptions of individual participants nor of their experiences. Lost are the nuances that qualitative approaches, methodologies, and paradigms can provide. Additionally, as these studies use surveys as the sole data collection tool, the questions asked may be interpreted in different ways by the participants and, may depending on literacy and situational or contextual factors, may be an inaccurate representation of what the participants really think, feel, and believe.

The tool was specifically designed for middle school learners in informal science experiences, thus the tool and the results derived from its implementation may not, and likely will not, transfer to other ages and would need to be modified to fit the disciplinary norms of other domains beyond science. The pre/post nature of the surveys were intended to gain an understanding of the impact of an informal science experience and the studies make no claims about the impact duration. Findings from a less structured environment may produce different results and opportunities that are longer or shorter will likely have different impact durations. Also, the middle school learners included in these studies are almost exclusively from rural communities. Their prior experiences with science and their overall engagement with science may be different than those from other communities, urban or otherwise. These issues are mitigated by sufficient sample sizes; however, the generalizability of the findings may still be best limited to other rural areas.

The tool is designed for informal contexts, and as such, likely will not be specific enough to work in formalized settings such as structured classroom activities. Particularly with self-regulation and self-efficacy, the domain specificity in an important aspect of the validity of these constructs. Other survey instruments are already designed for these spaces and should be considered prior to using the tool developed in this study.

Potentially the most important limitation is that the intent of the study is to understand the changes in cognitive engagement, motivation, and future aspirations in science and not to assess the quality, goals, or experiences provided in the informal science opportunities. The study will not provide a detailed account of all of the opportunities available to participants as the goal of the study is to look at exposure to science informally, not to make judgements surrounding quality.

Delimitations of the study range from decisions made by the researcher surrounding the conceptual model to the methodology to the analyses. First, as the basis for the research is in the literature base, it is important to note that the conceptual model does not include theories that are specific to formal settings including school engagement. Though a brief history of engagements' root in decreasing dropout rates is covered, the majority of the literature focuses on relatively recent developments with the concept as they are founded in theories that can apply to both formal and informal settings. Additionally, while there are ongoing debates concerning the boundaries between formal and informal settings, the conceptual model endeavors to cover much of the research and literature that has been conducted in informal settings. However, given the breadth of this task and the difficulty in ascertaining whether or not an intervention or opportunity is formal or informal, it is likely that studies that "walked this line" are not included in the review. One other important note is that a number of informal experiences do not have assessment procedures (National Research Council, 2009), let alone openly publishing the findings, thus limiting the overall status of the field. Finally, the methodological and analytical process used in these studies represent only one way to view the data collected from the surveys. The sample represented in this study was collected via a convenience sampling approach from predominantly rural areas. As such, the findings and results may not generalize in other populations. Additional analyses may yield alternative results concerning learner's prior experiences specific to an area or school, within group differences from Phase Two and/or different relationships amongst and within the latent constructs presented.

## Significance of Study

Despite the potential limitations and delimitations, this study will represent one of the first to operationalize and measure cognitive engagement and motivation in informal contexts. Learning in these contexts has the potential to influence the learner's knowledge of and self-efficacy in science (National Research Council, 2009) and provides avenues for exploration that are not typically associated with formal classroom contexts (Wellington, 1990). With mounting calls for individuals who are scientifically literate and interested in entering into STEM-based careers, exploring informal contexts for their potential to increase learner's interest and self-efficacy in science is a worthy endeavor. This study is intended to set the stage for additional approaches and methodologies to understand the complex nature of informal contexts by understanding how current theories of engagement and motivation transition into these settings and the potential for these settings to change learner's cognitive engagement, motivation, and future aspirations in science.

# CHAPTER TWO: REVIEW OF RELATED LITERATURE

As the construct has been touted as the “holy grail of learning” (Sinatra et al., 2015, p. 1), research on engagement has been growing. Its benefits are as multifaceted as the construct, as when learners engage, outcomes can include academic achievement, persistence towards high school graduation (Christenson et al., 2012), and a desire to pursue science in the future (Martin et al., 2016). Research on engagement has largely been limited to formal contexts. Yet, given the potential of learning in informal contexts (National Research Council, 2009), these environments are natural places to examine engagement (Tytler & Osborne, 2012).

Although affective and behavioral domains of engagement are important, cognitive engagement, with its close ties to motivation (Appleton, Christenson, Kim, & Reschly, 2006), may provide important links between informal and formal contexts (Bergin, 1996). Cognitive engagement describes a student’s self-regulation skills (Pintrich & De Groot, 1990) and use of diverse strategies in order to problem solve (Greene, 2015) and when linked with motivation, the desire and ability to complete tasks (Pintrich & De Groot, 1990), can become a powerful tool to address the complexities in the nature of science. In informal settings, learners engage in the process of learning science voluntarily (Falk, Donovan, & Woods, 2001), therefore it stands to reason that the learners motivational levels are likely high, which might foster problem solving skills. Lastly, in light of a drop-off of learner interest in science around middle school (Vedder-Weiss & Fortus, 2011, 2012), understanding how to engage learners in science at this time may be a way to encourage future aspirations in science, including a desire to pursue a career in science (President's Council of Advisors on Science and Technology, 2010).

The following literature review will be organized around the concept map (Figure 4). Concepts are presented in the rounded rectangles and are linked by arrows through the relationships presented in the literature, which may or may not contain a citation. The concept map is structured hierarchically, with large scale theories and context listed at the top, continuing down to methodological approaches at the bottom. Particular to, and bounding, this study are the colored constructs, going hierarchically: red, orange, yellow, green, blue, indigo, and violet.

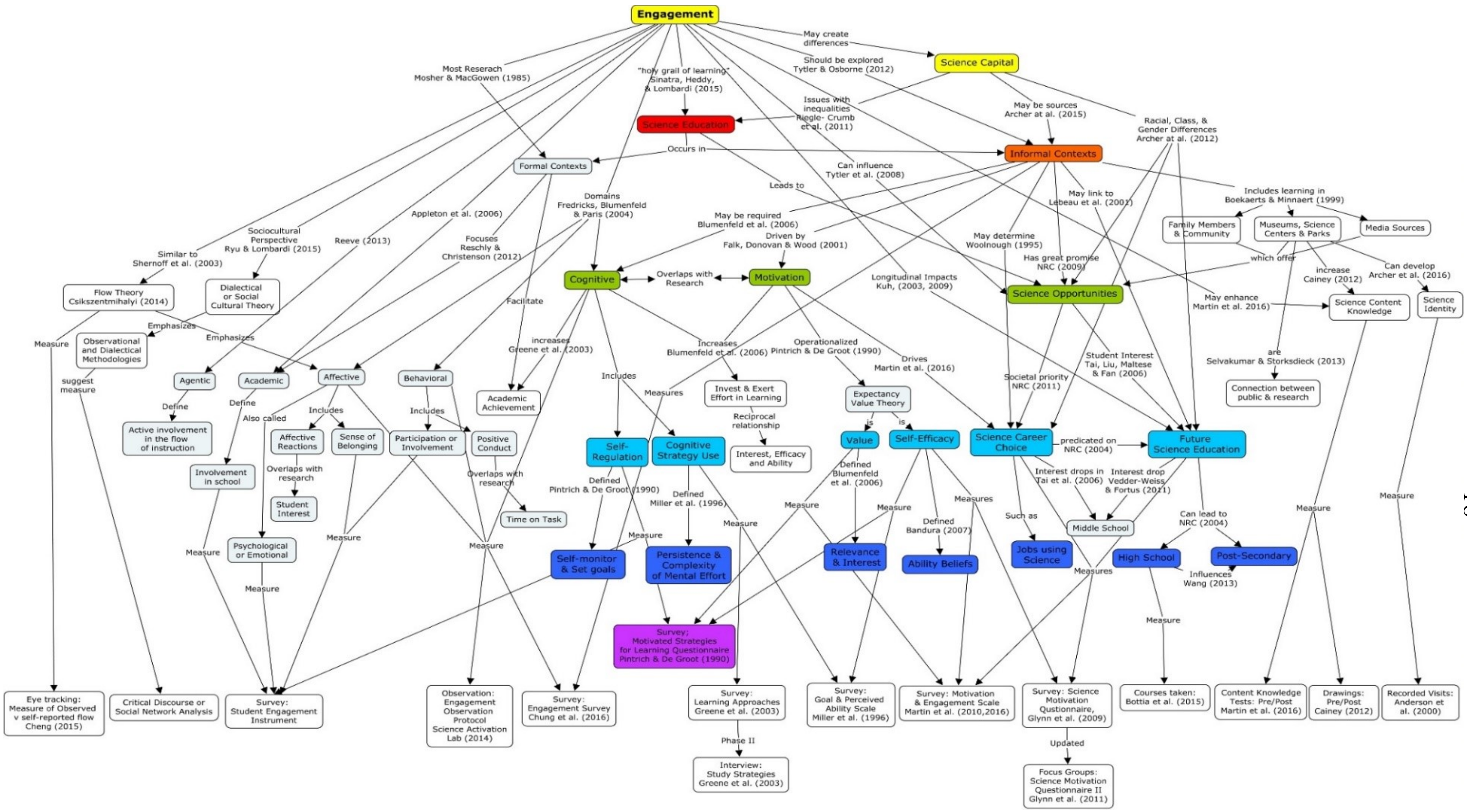


Figure 4 Map of the conceptual framework

## Engagement

Originally defined within school contexts, engagement and its opposite, disengagement or alienation, were used to discuss the factors that lead to students either completing or dropping out of school (Mosher & MacGowan, 1985). Especially within minority or low-income student backgrounds, student engagement has shown to be a strong predictor of student success with those that self-report high levels of engagement being more likely to persist and complete school (Reschly & Christenson, 2012). Student engagement is the glue, or mediator, that links important contexts—home, school, peers, and community—to students and, in turn, to outcomes of interest (Reschly & Christenson, 2012, p. 3), extending the notion of engagement outside the confines of school. This highlights the importance of out of school time, activities, and events in encouraging engagement in learning. Based on the theories surrounding engagement, a number of programs were designed to promote student persistence that included interventions such as long-term mentoring, consistent data-driven checks on behavior and student progress, as well as partnerships with the family (Appleton et al., 2006; Reschly & Christenson, 2012).

The aptly named book section, "jingle, jangle, and conceptual haziness" (Reschly & Christenson, 2012, p. 3), gets at the evolution of and the difficult boundaries of engagement since Mosher & MacGowan (1985). Whereas most definitions of engagement include aspects of a student's emotions, behaviors, and cognition, not all agree on the bounds or definitions of these constructs. For example, some scholars include academic engagement as a separate domain and may call affective engagement, psychological engagement instead (Appleton et al., 2006; Reschly & Christenson, 2012). Even further back in the literature, only two domains of engagement were recognized: affective and behavioral (Marks, 2000). Regardless of how the concept of engagement was parsed, it was likely that each of these domains are interrelated (Christenson et al., 2012). Given its “meta” nature, there are a number of additional concepts well explored in the literature that overlap with the current domains of engagement. For instance, affective engagement can overlap with research on interest (Baram-Tsabari & Yarden, 2009; Tai et al., 2006), behavioral engagement includes on-task behaviors (Gill & Remedios, 2013), and the lines between cognitive engagement and motivation can be seen as non-existent (Martin, 2008), highly interrelated (Greene & Miller, 1996; Miller, Greene, Montalvo, Ravindran, & Nichols, 1996), or separated, with motivation “considered to be intent and engagement as action” (Reschly & Christenson, 2012, p. 14).

Specifically, not included in this study are Appleton et al.’s (2006) academic engagement and Reeve & Tseng’s (2011) agentic engagement. The concept of academic engagement is limited to formal contexts as it is operationalized by attendance rates, grade point average (GPA), and other school-specific performance measures (Appleton et al., 2006). These categories seem to be influenced by a number of external forces outside the control of the student and appears to overlap with behavioral engagement with its focus on procedural ways measuring student behaviors akin to time on task. Agentic engagement involves the student’s active involvement in the nature or process of instruction (Reeve, 2013) and is operationalized by outward displays of feedback such as asking questions or expressing opinions. While these are worthy actions of students to help create agency (Arnold & Clarke, 2014), it is unclear how students of differing learning styles or preferences would approach and/or demonstrate agentic engagement as defined.

The most predominant framework arises from Fredricks, Blumenfeld, & Paris's (2004) work, defining engagement as compromising of three domains: affective, behavioral, and cognitive. Affective engagement involves the emotional reactions to the sociocultural context such as value, sense of belonging, and interest (Fredricks et al., 2004; Fredricks & McColskey, 2012). Behavioral engagement encompasses aspects such as time on task, voluntary participation, and involvement in activities (Appleton et al., 2006; Fredricks et al., 2011). Finally, cognitive engagement is seen as "less observable, more internal indicators" (Appleton et al., 2006, p. 429) and focuses on a level of investment in learning such as self-regulation (Pintrich & De Groot, 1990), cognitive strategy use, and persistence (Greene, 2015; Greene & Miller, 1996).

Another theory closely related to engagement is flow theory (Csikszentmihalyi, 2014). Flow describes a, "deep absorption in an activity that is intrinsically enjoyable…[where] the individual functions at his or her fullest capacity… (Shernoff, Csikszentmihalyi, Schneider, & Shernoff, 2003, p. 160). It is a combination of student concentration, interest, and enjoyment, categories which may be akin to behavioral and affective engagement. In Shernoff et al (2003)'s study, students experiencing flow where more likely to be engaged. However, the definition of engagement within this study is limited and is operationalized as not dropping out and high involvement in class rather than using distinctive affective, behavioral, and cognitive cues. Interestingly, however, is that the study also found profound effects on engagement when students found learning activities both cognitively challenging and within their abilities (Shernoff et al., 2003, p. 171). These findings seem to suggest that when students use diverse cognitive strategies (an aspect of cognitive engagement) and feel that they are capable of completing the task (self-efficacy, an aspect of motivation), they benefit academically. As such, while flow theory may be a useful parameter to look at specific interventions, engagement may be a better construct to explore when looking at broader or encompassing phenomenon.

In contrasting engagement and flow theory, it is useful to look at what Sinatra et al. (2015) call "grain-size," as it provides one approach towards dealing with the conceptual uncertainty surrounding engagement. By looking at the differing levels at which the concept can be defined and operationalized (varying "grain-sizes), research can begin to gain clarity. First "researchers must decide if they are defining engagement as behavioral, cognitive, or emotional, or some combination of multiple dimensions…" and, then, choose a method by which to measure it that aligns with the "researchers' choice of theoretical framework and research question of interest" (Sinatra et al., 2015, p. 7). Though potentially a routine suggestion, it is clear through the varying ways in which engagement has been studied in the past, that these basic suggestions are critical to selecting appropriate theory bases and measures from existing literature (Fredricks et al., 2011; Sinatra et al., 2015). For example, when understanding whether a specific activity interests a learner, such as the efficacy of a particular digital game-based learning (Cheng, 2015; Hamari et al., 2016; Tsai, Huang, Hou, Hsu, & Chiou, 2016), flow theory may be a better theory to describe this small grain size.

Understanding a study's "grain size" becomes all the more important when looking to understand individual definitions of engagement. Some studies use the term engagement in different ways, such as those that combine it with motivation (Martin, 2008, 2012), or those that measure all dimensions in one survey (Chung, Cannady, Schunn, Dorph, & Bathgate, 2016). Many studies investigate set aspects of each domain such as the *Goal and Perceived ability scale* (cognitive strategy use, goal-settings, and self-efficacy; (Miller et al., 1996) and the *Motivated Strategies for Learning Questionnaire* (self-regulation, self-efficacy, and value) (Pintrich & De Groot, 1990).

An important note is, much as emphasized by Greene (2015), the majority of research into engagement, and by extension cognitive engagement, has been conducted using self-report surveys. There are a number of calls for expanded methodological approaches (Azevedo, 2015; Ryu & Lombardi, 2015), yet only a few studies have currently gone beyond survey measures. Two studies include interviews and focus groups along with surveys to look at instrument validity and reliability (Glynn, Brickman, Armstrong, & Taasoobshirazi, 2011; Glynn, Taasoobshirazi, & Brickman, 2009; Greene, Dillon, & Crynes, 2003). A number use observational methods (e.g. Archer et al., 2016; Ayar, 2015; Eilam & Reiter, 2014). Other construct, as either predictors or outcomes, used in studies that include engagement or related theories include: high school courses taken (Bottia, Stearns, Mickelson, Moller, & Parker, 2015), numerous demographic variables (Kuh, 2003, 2009) pre- and post-content knowledge tests (Martin et al., 2016), audio recorded experiences (Anderson, Lucas, Ginns, & Dierking, 2000), eye-tracking (Cheng, 2015), and pre-and post-drawings (Cainey, 2012). While the different methodologies used to explore engagement, it is important to keep in mind the arguments of Bamberger and Tal (2009) who's work using multiple methodologies to understand learning in museums show that multiple methods do not necessarily provide evidence towards the reliability and validity of the another. Rather, that survey, interview, or other methodologies respond to different aspect of an experience and, in essence, answer different questions (Bamberger & Tal, 2009, p. 127).

Cognitive aspects of engagements are a focus of this study because, like Greene (2015), "our interest [is] on how cognitive engagement could help us understand motivation to learn and achievement" (p. 15). While recent engagement research has focused on measures associated with behavioral and affective domains, there has been less research on cognitive engagement despite the suggested connection between it and school performance (Appleton, Christenson, Kim, & Reschly, 2006; Spanjers, 2007). Further, within the context of informal learning environments, both affective and behavioral engagement may play a less important role as these are voluntary, and largely self-driven learning contexts (Falk, 2005; Falk et al., 2001; Falk et al., 2007). Should learners not be affectively or behaviorally engaged, they are free to move, drive their energies in alternative directions, or stop the process entirely.

Defining cognitive engagement clearly is a matter of concern as the construct can be easily confused with existing literature bases, notably motivational research. To this point, Reschly and Christenson (2012) share that, "it is possible that cognitive engagement and motivation are in fact very similar… motivation is considered to be intent (internal) and engagement as action (observable)" (p. 14). For the purposes of this study, cognitive engagement refers to the degree of investment in learning and revolves around learner's ability to self-regulate and to use thoughtful and strategic ways to meet the complexity of the skills being learned and is considered to be determined by a learner's motivation (Fredricks & McColskey, 2012, p. 764).

## Motivation

Regardless of the cognitive strategies known and used by a student to engage in the process of learning, they must first be motivated in order to use these abilities (Blumenfeld et al., 2006; Pintrich & De Groot, 1990). Though there continues to be a debate concerning the difference between engagement and motivation (e.g. Christenson et al., 2012), motivation is "often present implicitly or explicitly in most characterizations of engagement" (Sinatra et al., 2015, p. 2). Intriguingly, some researchers have chosen to combine and discuss them as a single unit of engagement and motivation (Martin, 2008).

Motivation in science can impact the degree to which students pursue science in the future (Martin et al., 2016; Sha, Schunn, Bathgate, & Ben-Eliyahu, 2016). Self-efficacy has been shown to influence student choice of science-related activities as well as their persistence in these activities (Martin et al., 2016, p. 1365). Together with value, self-efficacy has been shown to predict future STEM coursework aspirations (Guo et al., 2017) and is related to career aspirations (Aschbacher et al., 2014; Hulleman & Harackiewicz, 2009). Additionally, "as students' perceived ability increased, so did their judgement of the value of the information being learned" (Miller, Behrens, Greene, & Newman, 1993, p. 3). Taken together, continued research on motivation (via constructs such as self-efficacy and value) are likely to provide insights into improved strategies designed to foster student's future aspirations in STEM.

## Science Capital

Despite decades of work dedicated to increasing opportunities and representation in the STEM fields, persistent inequalities remain (Baker, Rilett, Kunz, & Nugent, 2014; National Science Board, 2015; National Research Council, 2011; Smith, 2011). From differences in socioeconomic status (SES) (Aschbacher, Li, & Roth, 2010) and racial and ethnic minorities (Archer et al., 2012; Huang, Taddese, & Walter, 2000), there is unequal participation in post-compulsory STEM education and persistence into STEM-careers. This is problematic both in light of the importance of STEM to global competitiveness (President's Council of Advisors on Science and Technology, 2010) as well as the potential loss of new perspectives that increased representation could bring to the culture of science (Aschbacher et al., 2010). In addition, "the imperative to improve participation reflects both national economic concerns… and social justice concerns, to promote equity and ensure a scientifically literate general population who can be active citizens within a scientifically advanced contemporary society" (Archer et al., 2015, p. 923)

As championed by Archer et al. (2012), returning to the work of Pierre Bourdieu may provide a new lens by which to both discuss and conceptualize these persistent inequalities in science participation. Bourdieu' writings attempt to describe the patterns and structures by which a society creates and maintains inequality. Succinctly put,

> Bourdieu proposes that relations of privilege and domination are produced through the interaction of habitus with capital (resources—which can be

> economic, cultural, social, and symbolic) and field (social contexts) (Archer et al., 2012, p. 884).

As an example, Lareau (2011) shares the story of a child born to an ethnically-diverse couple in an urban area. The child's school has a few budgetary issues and pays teachers less than the surrounding suburban areas despite a reputation to be have more difficult teaching conditions. Resulting from the combination of factors, the child is less likely to receive special education services, and because test scores are falling overall in the school, there is pressure on the teachers and administrators from the community. Though the conditions (fields) present are not the fault of the student, they inherently impact the student's life. The economic issues present in the community (low capital), make it difficult to provide the child with a good education. Further, as a result of the perceived poor education, there is low familial input and value based on the institution (habitus).

A critical part of Bourdieusian theory is the notion of capital as a valued resource that can create an advantage in a given field. While the concept of capital continues to be expanded into avenues outside of Bourdieu's (1986) social, economic, material, and symbolic realms, the concept remains bound to the field in which it interacts, in other words, it is a contextually-linked construct. Within education, a number of studies have explored how capital can be used to promote academic achievement and opportunity in light of the different educational experiences of students based on their gender, race/ethnicity, and class (Archer et al., 2016; Dika & Singh, 2002). As the pace of scientific progress in society is rapidly changing, extending the concept to include other extensions of capital, such as science-related capital, may enable a new perspective on the concerns around participation and representation in STEM fields and careers (Archer et al., 2015; Prieur & Savage, 2013). In their study around science-related capital, Archer et al. (2015) found inequalities in science capital between differing genders, ethnicities, and socioeconomic levels. However, their research suggests that where underrepresented populations are able to draw on science-related capital, it begets opportunities to obtain more science-related capital, which may foster future aspirations in science, regardless of socioeconomic status (Archer et al., 2015, p. 924).

Stressed by Archer et al. (2012), the intersection of habitus (expectations), field (context), and capital (resources or valued connections) can foster future aspirations in science, however, these are not deterministic. A student may still persist in the face of low social capital with a strong pro-science familial habitus to see themselves as scientists (future aspirations in science), yet the number of students who surmount these challenges will be limited. Therefore, "there is an urgent need to address the disparity in the societal distribution of science capital… more needs to be done to make science a 'thinkable' career option for all" (Archer et al., 2012, p. 904).

Calls for increasing participation in science have looked to informal contexts to help decrease the gaps found in formal education (Jones, 1997). Informal science opportunities have been shown as ways to connect learners to science in ways that formal contexts have not (Russell, Knutson, & Crowley, 2012), particularly for underrepresented learners (Jones, 1997). Deemed as "third spaces—that is, spaces that can promote science learning and engagement through the reworking and refiguring of science in ways that are more relevant and equitable for urban young people" (Archer et al., 2016, p. 441), informal learning contexts differ from formal contexts in that they engage learners in alternative ways (Stocklmayer, Rennie, & Gilbert, 2010, p. 25).

## Future Aspirations in Science

With the increasing importance of STEM fields in society (National Academies of Sciences, Engineering, & Medicine, 2016) it is potentially more important than ever to foster students' interest in and desire to pursue STEM-related careers (Henriksen, Dillon, & Ryder, 2014). For example,

> [STEM-based skill sets] open the door to jobs, strengthening the backbone of American ingenuity, driving solution to complex problems across industries, and improving lives around the world…today, too many of our Nation's K-12 and post-secondary students lack access to high-quality STEM education" (The White House, 2017, p. Section 1).

However, beyond career aspirations, solid educational experiences in STEM provide a foundation to understand a complex and technologically advanced contemporary society (Archer et al., 2015). With growing environmental challenges, "the health of our planet rests in increased public understanding of science…achieving this depends on inspiring more young people to value and desire to learn science" (Cacciatore & Sevian, 2011, p. 248).

Future aspirations, such as the desire to take additional coursework or career aspirations, have been connected to cognitive engagement (Hazel, Vazirabadi, & Gallagher, 2013), motivation (Harackiewicz, Rozek, Hulleman, & Hyde, 2012; Reeve, 2012), or as more related to student interest or attitudes (Riegle-Crumbet al., 2011; Tai et al., 2006). Higher levels of motivation and engagement have been shown to increase the likelihood of students taking more advanced, formal coursework (Glynn, Brickman, Armstrong, & Taasoobshirazi, 2011; Green, Martin, & Marsh, 2007; Meece, Wigfield, & Eccles, 1990; Potvin & Hasni, 2014). For this study, future aspirations include indicators of 1) the degree to which the middle-school participants wanted to take future science courses (National Research Council, 2004), 2) learner interest in science (Archer et al., 2012; Tai et al., 2006), and 3) learner desire to pursue careers in science fields (Christensen, Knezek, & Tyler-Wood, 2014; Tyler-Wood, Knezek, & Christensen, 2010).

## Learning Contexts

> Contrary to the pervasive idea that schools are responsible for addressing the scientific knowledge needs of society, the reality is that schools cannot act alone, and society must better understand and draw on the full range of science learning experiences to improve science education broadly (National Research Council, 2009, p. 12).

An overwhelming number of researchers and practitioners show that commonplace and everyday experiences influence how people learn and understand science, and the degree to which they identify as scientists (National Research Council, 2009). Although speaking of informal and formal contexts as separate entities likely oversimplifies the complex nature of learning, it may be useful to discuss them as dichotomous variables when looking at the far ends of learning contexts. Learning in informal contexts is free-choice, voluntary, and internally or learner-driven (Falk et al., 2001; Stocklmayer, Rennie, & Gilbert, 2010). Increasingly, informal science environments have been highlighted for their potential to improve science understanding and participation in daily science activities and scientific careers (Ayar, 2015; National

Research Council, 2011; National Research Council, 2004, 2009). There are many good reasons for this, which include engagement, fun, and self-directed learning (Falk & Dierking, 2000; Falk et al., 2001; Falk & Storksdieck, 2005; Little, Wimer, & Weiss, 2008), qualities that often stand in contrast to traditional formal school experiences (National Research Council, 2009). To reiterate, learning that occurs in these spaces is voluntary not compulsory (Wellington, 1990).

As analyzed in the review completed by Stocklmayer, Rennie, and Gilbert (2010), the very defining characteristics of informal environments are what enable them to be successful, flexible, and inclusive learning experiences. Learning that takes a, "more holistic approach to science education, one that better integrates school, work and leisure time [informal] learning experiences … could be a more robust approach to long term gains in public understanding of science" (Falk et al., 2007, p. 464). However, these unique informal learning characteristics also, in part, pose challenges to developing a deeper understanding of science content and practices (McManus, 1994) due to learning that occurs in typically short, sporadic visits (National Research Council, 2009). The impact of these experiences will shift over time as a function of the learners' contextualization of the knowledge (Falk & Dierking, 2000). In this way, learning in informal contexts might resemble a stochastic model, wherein learning becomes dependent on a number of unknown or unaccounted for variables which mitigate and influence the final quality and quantity of learning (Falk & Storksdieck, 2005, p. 771).

Informal contexts are of growing importance within science education as a result of their unique ability to reach people at every age and due to the fact that the majority of any persons' time is spent outside of the classroom (National Research Council, 2009). Drawing on Falk, Donovan, and Woods's (2001) work on free-choice learning, informal contexts are powerful learning environments because they enable the individual to direct the learning process. As a result of this highly individualized approach, documenting learning in informal contexts is difficult as it requires measures that go beyond a simple behaviorist view of assessment such as those that measure content knowledge gains through concrete and prescribed interventions (National Research Council, 2009; Sinatra et al., 2015).

As cognitive engagement and motivation are rooted in a degree of investment- both in how thoughtful and how willing the participant is to persist despite task difficulty- it follows then that informal contexts may be rich sources of cognitive engagement and motivation research. If learners choose the learning context and process, their motivational levels may already be high (Lebeau, Gyamfi, Wizevich, & Koster, 2001). Lebeau et al. (2001) state that, "further investigation is warranted to examine any relationships that may exist between [informal learning] and student persistence and effort in formal science learning settings" (p. 142). Additionally, Blumenfeld et al. (2006) argue that stepping away from traditional environments may be what is necessary to encourage learners to become more cognitively engaged as factors outside of the classroom influence the behavioral, affective, and cognitive aspects of a learner's life, a suggestion supported by Woolnough's (1994,1995) work, showing that many learners see out-of-school activities as a determining factor in their desire to pursue STEM careers.

Despite the potential for informal science learning contexts to influence learner engagement and attitudes beyond informal contexts, little research explores this potential link (Bathgate, 2015; Tytler & Osborne, 2012). Tytler and Obsorne (2012) suggest "considerable anecdotal and weak evidence that student learning and engagement in science are enhanced by participation in enrichment activities… but there is a need for further research into the impact of these public science resources on student attitudes to and engagement with science" (p.617-618). To this end, though there is a growing body of literature and associated scales related to measures of cognitive engagement and motivation in science within formal contexts, few such measures exist specific to informal settings. One recent "Engagement in Science" instrument (Chung, Cannady, Schunn, Dorph, & Bathgate, 2016) measures affective, behavioral, as well as cognitive engagement generally, whereas this study specifically focuses in on cognitive engagement.

## Summer Camp Learning Experiences

Fascinatingly, it has been said that 75% of Nobel Prize Winners in the sciences name informal experiences as the root of their interest in science (Friedman & Quinn, 2006). Further, many learners who pursue careers in the STEM fields attribute their success to programs that occur outside the bounds of school (Baguio, Fowler, Ramirez, & Györgyey Ries, 2015).

From an early age, children learn informally at first through modeling and observation, yet as children grow and develop, they may choose to engage in the learning process much more autonomously. Particularly in informal spaces, learners are encouraged to take agency in the process (Falk et al., 2001) and, increasingly, opportunities are available for learners in the summer time. Often, these camps are offered in partnership with an institution of higher education (Kleinert, 2009; Smith-Palmer, Schnepf, Sherman, Sullenger, & MacDonald, 2015), and provide interactions between practicing scientists and/or professors, who act as models to show participants the process of thinking like a scientist (Cacciatore & Sevian, 2011).

# CHAPTER THREE: METHODOLOGY

## Researcher Positionality

While not typically associated with quantitative research, positioning the researcher within the study may assist in contextualizing the methodological and analytical approaches used in this study. This statement is not to create a hegemonic relationship amongst different paradigmatic approaches to engagement research, rather to provide a lens by which to perceive the study findings within the larger context of engagement research.

People can feel strongly about certain issues to the point where they may feel those opinions are, in fact, truths. “If researchers are to contribute to the improvement of education…they need to raise their sights a little higher than expressing their fervent beliefs or feelings of personal enlightenment, no matter how compelling these beliefs are felt to be” (Phillips & Burbules, 2000, p. 3). It must be a goal of the researcher, through multiple measures to parse out personal bias, to seek knowledge. Without this goal, research will almost always lead down path of personal opinions, accepting partial if not flawed truths. Acknowledging the fallibility of the human condition, striving to understand the truth enables a constant revision of knowledge. “If we keep trying, we will eventually discover whether or not the beliefs we have accepted are defective, for the quest for knowledge is to a considerable extent “self-corrective” (Phillips & Burbules, 2000, p.3).

As such, with this study, creating a measure of cognitive engagement and motivation in informal contexts does potentially necessitate a revision of knowledge specific to formal contexts. The theories, constructs, and discussions surrounding these topics occurred under the structured nature of formal educational systems as seen with the very roots of the term engagement describing the factors that keep students from dropping out of school (Fredricks et al., 2004). Testing whether these theories hold true then continues in Phillips & Burbules's (2000) "quest for knowledge."

In order to parse out personal opinion, the study has minimal researcher and participant interaction intended to both minimizing the impact of the research on the learner's experience and lessen the impact of researcher biases.

## Introduction

This chapter will outline the various methods used in both phases of the study. To ensure methodological coherence, Table 1, shows the relationships between the research questions and methods presented in the chapter. Included in this chapter are the methods, sample characteristics, data collection tools, and data analysis techniques.

Table 1 Overview of research questions, data acquisition methods, and data analysis techniques

| Phase 1 | | |
|---|---|---|
| Research Question | Data Acquisition Methods | Data Analysis Technique |
| What survey questions operationalize cognitive engagement and motivation in science specific to informal contexts for middle school learners? | Survey | Correlation, Factor analysis, Partial-least squares structural equation modeling |
| What impact does informal science experiences have on middle school learner's future aspirations in science? | Survey | Paired samples t-test |

Table 1 Continued

| Phase 2 | | |
|---|---|---|
| Research Question | Data Acquisition Methods | Data Analysis Technique |
| What survey questions operationalize cognitive engagement and motivation in science specific to informal contexts for middle school learners? | Survey | Correlation, Factor analysis, |
| What impact does informal science experiences have on middle school learner's future aspirations in science? | Survey | Paired samples t-test |
| As a result of an informal science experience, what is the relationship between middle school learner's cognitive engagement and their gender, race, and socioeconomic statuses? | Survey, Program Application | Multivariate analysis of variance |
| As a result of an informal science experience, what is the relationship between middle school learner's value of science and their gender, race, and socioeconomic statuses? | Survey, Program Application | Linear Regression |
| As a result of an informal science experience, what is the relationship between middle school learner's self-efficacy in science and their gender, race, and socioeconomic statuses? | Survey, Program Application | Linear Regression |
| As a result of an informal science experience, what is the relationship between middle school learner's future aspirations in science and their gender, race, and socioeconomic statuses? | Survey, Program Application | Linear Regression |

## Methods

The primary method being used to assess cognitive engagement, motivation, and future aspirations in science in both quantitative studies is survey research, wherein participants self-report numerical representations of their attitudes (Creswell, 2014). While there are calls for the field to move beyond self-report data (Greene, 2015), cognitive aspects of engagement are largely internal processes (self-regulation and cognitive strategy use), therefore external measures such as observations are difficult and would measure proxy behaviors or verbal responses. Additionally, as research on engagement is almost exclusively limited to formal schooling endeavors, a survey of these factors in informal settings provides an easy baseline dataset to test how well the theories surrounding engagement and motivation transfer to different contexts. An important note is that the context in which the study was conducted was not designed or encouraged to promote cognitive engagement, motivation, or future aspirations in science. All of the methods, analysis, and results are intended to understand the ability of informal contexts to promote these skills and beliefs without a specific intervention, rather to understand if these contexts naturally support their development.

Any methodology, being it self-report or otherwise, has drawbacks or limitations. For example, qualitative or other non-self-report approaches are subject to observer implicit biases that will limit the findings (Sinatra et al., 2016). As evidence of value, Bamberger and Tal's (2009) work shows that survey measures, as opposed to open-ended questions or interviews, focus in on different aspects of learning in informal contexts and may be able to uncover connections to learning not immediately apparent to the participants.

While there are a number of surveys already in the literature that measure aspects of engagement and motivation (Appleton et al., 2006; Miller et al., 1996; Pintrich & De Groot, 1990), it is possible that many of these surveys lack conceptual clarity (Sinatra et al., 2015, Reschly & Christenson, 2012). For formal contexts, the report by Fredricks and McColskey (2014) outlines a number of studies on self-report measures of engagement specific to middle school students. Unfortunately, many of the studies identified lack sufficient information to reproduce the survey, such as providing the actual survey questions. Only half of the 21 items identified by Fredricks and McColskey (2014) measure cognitive engagement, 6 of which are proprietary in nature, with costs associated with obtaining the survey instrument. Three of the remaining surveys were used in the construction of our survey instrument as evidence of construct validity. Only one survey has been specifically designed and implemented in informal contexts specific to engagement (Chung et al., 2016) prior to the onset of this research study. Yet, sadly, this instrument has issues with domain specificity (Bandura, 2006; Sinatra et al., 2015) as it is not contextually or disciplinarily-bounded, and the exploratory factor analysis conducted on the data shows that there may be some issues with discriminant validity due to cross-loaded items (loading over 0.32 on multiple factors; (Costello & Osborne, 2005).

Potentially most important, however, is that as a result of the literature having little precedent for exploring engagement in informal contexts, it is paramount to ensure that the informal nature of the experience is maintained, and the methodologies used in the study do not impede the experience thereby avoiding over-formalization (Yoon, Elinich, Wang, Van Schooneveld, & Anderson, 2013). Over-formalization arises when the amount of scaffolding in a learning environment restricts the exploration and nature of an informal learning experience (Yoon et al., 2013). Surveys can be effective ways to obtain information with little impact on the participant, and the instrument created in this study is short and disseminated at key points during the experience to minimize the impact on participants.

## Site Selection

Out of school science experiences have the potential to help learners retain and/or gain interest in STEM as these settings are largely driven by learner choice (Falk et al., 2001; National Research Council, 2009) and summer camps have great potential to achieve these goals as a result of their connection to STEM mentors (Cacciatore & Sevian, 2011; Smith-Palmer et al., 2015). To this end, the study was completed with middle-school participants entering fifth through eighth grades in two distinct, week-long, informal science camps held at a four-year public university located in the Rocky Mountains, USA over the course of two years (2016, 2017; Phase One and Two, respectively (Figure 5.).

## Sampling Procedures

Participants in these summer camp experiences were selected for this study as a result of their grade levels (Vedder-Weiss & Fortus, 2011, 2012), and as they are a diverse group of individuals from across the state. Many of the learners in the first camps

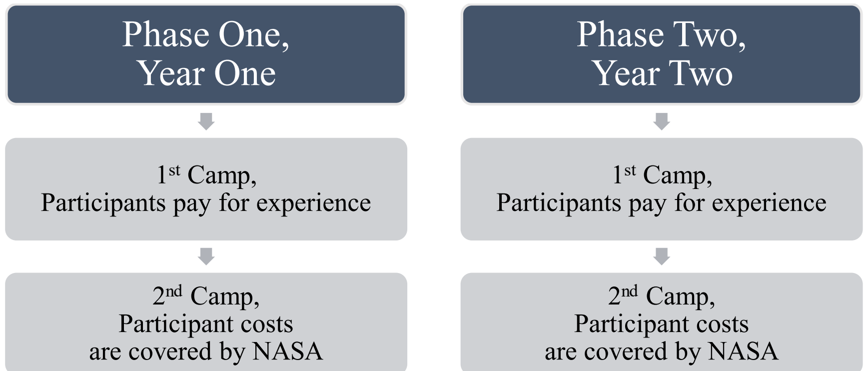


Figure 5 Overview of the study context and sample

come from areas closer to where the camps were held (up to 75% both years), whereas learners in the second camp were predominantly from across the state with no more than 7% coming from the same city as the university. Also, in the second camp, for both years, no more than 20% of the learners came from the same city, another indicator of their diversity in comparison to the first camps. However, despite their diversity, the learners included in this study were not randomly selected, rather they self-selected to attend this experience. Therefore, the samples for both Phase One and Phase Two follow a convenience sampling approach, which limits the generalizability of findings of this study overall as this sample may represent a unique population not found outside of the context of this particular study. Random selection of the sample would have ensured greater generalizability of the findings, however, is impractical for this study.

All camps featured three science sessions every morning and learners were allowed to choose which three sessions they attended for the week based on their personal interests and availability. Each science sessions each lasted 90 minutes each day and included a variety of topics such as carbon cycle literacy, water quality, embryology, and bacteria for a total of four and a half hours of science experience each day. Learners spent the remainder of each day participating in outdoor activities, sports, or open recreation time.

One distinguishing feature between the two camps offered during each of the two Phases included in this study is the residential focus of the second camp. For the first camp, some learners commuted daily, and some stayed overnight whereas, for the second camp, all learners stayed overnight in the campus dormitory facilities. This distinction may be important as the learners in overnight residence may have a greater opportunity to adjust to the surroundings and, therefore, be more comfortable to take risks in the activities. However, this claim is anecdotal and would need empirical testing to confirm.

## Phase One and Phase Two Studies

For the following sections, Phase One and Phase Two will be presented independently. Starting with phase one, the sample, data collection strategies, and data analysis techniques will be presented first followed by the same information for Phase Two of the study.

### Sample, Phase One

Each of the 152 learner participants in both of the camps had to formally apply for one of the camps (79 in the first camp, 73 in the second camp). The camps accepted students on a first-come, first-serve basis. Of the 152 learners, 41% were female, and the average age was between 11-12 years old. The survey tool did not ask for learners to provide this information as they had also completed an application to attend the camp. However, upon further investigation after the camp, the initial applications did not ask for participants to provide these demographic indicators. Thus, for Phase One, no information concerning the learners race or ethnicity was collected during the summer camps. The learners school's title 1 status level was used a proxy for individual socio-economic status (Cowan et al., 2012) and are identified as either not eligible, eligible not participating, targeted, or school-wide (Montana Office of Public Instruction, 2017).

For the first camp, the application process was brief, consisting of one page in which the learner and parent(s) completed contact information and ranked their preferred science sessions. Most importantly, campers paid $429-$644 in tuition to participate in the camp depending on the number of meals and overnight accommodations requested. Of the learners in the first camp, 9% of the learners are enrolled in schools who receive school-wide Title 1 funds, a federal program aimed at providing schools with funds to provide academic support for low-income students (Montana Office of Public Instruction, 2017a, 2017b). By contrast, the learner application process for the completely subsidized second camp was more rigorous, with the same contact information and session rankings, but also a learner letter of intent and two letters of recommendation, one of which had to come from a teacher. Funding for the second camp was made possible via NASA's Northwest Earth and Space Science Pipeline project. Almost 60% of the learners in the second camp (N=66) are enrolled in schools receiving school-wide Title 1 funding (Montana Office of Public Instruction, 2017a, 2017b).

Pre-survey response rates (n=150) were 99%, while post-survey response rates (n=146) were slightly lower (96%). Participants were only included in the study if they completed both the pre- and post- survey entirely, leaving a final sample of 140 used in analysis. The camps were combined as there were no differences in how students responded on the pre-survey items using an independent samples t-test ($p < 0.001$) after a Bonferroni correction, as t-tests are subject to family-wise error rates (Armstrong, 2014). Given to the entire population of 10-14-year-old children in the state in which the study is situated (69,298 people; U.S. Census Bureau, 2000), the sample size (N = 140) has a confidence interval is 8.27 at a confidence level of 95% (Creative Research Systems, 2012) in Phase One.

Table 2 Phase One participant demographics

| | 1st Camp | 2nd Camp | Phase One Total |
|---|---|---|---|
| Total Participants | 75 | 65 | 140 |
| Gender | | | |
| Female | 32 | 25 | 57 |
| Male | 43 | 40 | 83 |
| Other | 0 | 0 | 0 |
| Age | | | |
| 9 | 5 | 0 | 5 |
| 10 | 24 | 1 | 25 |
| 11 | 30 | 15 | 45 |
| 12 | 16 | 28 | 44 |
| 13 | 0 | 20 | 20 |
| 14 | 1 | 1 | 2 |
| Title 1 School Status | | | |
| Not Eligible | 8 | 0 | 8 |
| Eligible, Not Participating | 31 | 2 | 33 |
| Targeted | 23 | 24 | 47 |
| School Wide | 7 | 39 | 46 |
| Not applicable | 6 | 0 | 6 |

Data Collection Strategies, Phase One

During Phase One, a self-report survey instrument was developed to measure middle school learner self-efficacy, value, self-regulation, and cognitive strategy use called the Informal Cognitive Engagement and Motivation in Science (ICEMS) survey (Appendix A). To establish initial reliability and validity of this tool, evidence of the tools validity (construct- related and predictive) and reliability (internal consistency) will be presented in the results section. However, during the development of the ICEMS survey, steps were taken to ensure the construct validity of the survey.

First, the tool created in this study was based heavily on two reliable and validated surveys, the *Motivated Strategies for Learning Questionnaire* (MSLQ; Pintrich & De Groot, 1990; Pintrich, Smith, Garcia, & McKeachie, 1993), and the *Motivation and Strategy Use Surv*ey (Greene & Miller, 1996; Miller et al., 1993). The survey questions used were adapted, with indicators of time, subject, and activity being added to survey items to increase the specificity of the instrument and to fit the informal context (Sinatra et al., 2015). For example, one survey item, "When reading, I try to connect the things I am reading about with what I already know" (Pintrich & De Groot, 1990, p. 40) was modified to "This week, I thought about how new science activities relate to things I already know." This type of modification was made because the informal setting under investigation in this study emphasized hands-on learning and not reading. Items for value, self-efficacy, cognitive strategies, and self-regulation are adapted from Pintrich & De Groot's (1990) MSLQ with the exception being a measure for community relevance. This item was included because when learners can take responsibility for work that will benefit their communities, it enhances the personal relevance of schooling in general (McLaughlin, 2000, pp. 7-8) and, therefore, is an important aspect of learner motivation.

Second, the instrument went through several rounds of critique based on the conceptual framework with a review panel. Each item was reviewed for understandability and relevance based on the theoretical basis for cognitive engagement, motivation, and future aspirations in science. Changes to the survey items in this process focused heavily on the future aspirations in science. For example, the survey item, “I want to take more high school classes, “arose from conversations about the low state-based requirements of two years of science course for graduation. As the literature has shown that taking more advanced coursework is an predictor of future aspirations in science (Glynn, Brickman, Armstrong, & Taasoobshirazi, 2011), the survey item was created and included by the panel. The items displayed suitable readability (Flesch-Kincaid Grade Level, 5.7; Miscrosoft, 2016) and, ultimately resulting in the final ICEMS survey that was deployed in a pre- and post- manner with middle school participants. The full pre- and post-survey items used in Phase One of the study are provided in Appendix A.

The pre- and post-surveys contained two questions to link participants with the demographic information collected in the applications for the camps and 25 Likert-style questions, asking the learners to rate items on a 5-point scale (1=No, 2=Probably no, 3=Maybe, 4=Probably yes, 5=Yes). The differences between the pre- and post-ICEMS surveys were time scale and verb tense changes. For example, one item on the pre-ICEMS survey read, “I expect to do well on the science activities this week,” while the corresponding post-ICEMS survey read, “I did well on the science activities this week.”

Following survey development, the ICEMS instrument was administered to the two camps using an online survey program, Qualtrics (2015), via mobile devices (Apple, 2012). Importantly, surveys were administered in a manner to minimize the impact that the assessment has on the learner's experience in informal contexts (Yoon, Elinich, Wang, Van Schooneveld, & Anderson, 2013). First, the ICEMS survey was brief, containing only 25 questions. Second, the pre-survey was given while learners were checking into the camp and the post-surveys were administered during the final lunch prior to learners leaving for the week. The timing of the survey administration ensured that learners did not have to miss aspects of the informal science summer camp.

## Data Analysis Strategies, Phase One

The data collected for Phase One of the study was analyzed using correlational analysis, factor analysis, partial-least squares structural equation modeling, and paired sample t-tests, as set forth in the introduction (Table 1). First, the data was analyzed for normality and did not meet the assumptions for normality following a Shapiro-Wilks test. Next, correlations were conducted to explore the relationships between the survey items, noting areas of high and low correlation to address any issues with either low correlation or multicollinearity. Once evaluated, a factor analysis was conducted using the pre-survey data to understand the underlying structure, a step in identifying the latent constructs. A principle components analysis was conducted using Varimax rotation. From the results, five factors were retained and accounted for approximately 65% of the variance present in the pre-survey data.

Based on the factor structure, a structural equation model was generated. Structural equation modeling (SEM) is a mutlivariate statistical analysis technique that includes latent, or unobserved variables to be included in the analysis through the measured indicator variables (Hair, Hult, Ringle, & Sarsedt, 2014). SEM uses path models in order to display and test the relationships between the latent variables. There are two main types of SEM, one being more exploratory (partial-least squares) and the other confirmatory (covariance based). Covariance based SEM is appropriate for use in confirming a model and empirically testing the ability of the proposed model to explain the variance in the data set. It measures model fit and would be well suited to studies that are re-testing existing theories or looking to confirm previous studies. PLS-SEM should be considered, "in situations where theory is less developed… [and is] the preferred method when the research objective is theory development" (Hair et al., 2014, p. 14). Rather than covariance-based structural equation modeling, PLS-SEM's partial least squares regression method maximizes the $R^2$ values, thus making it ideal to use in applications where explanation of variance is a main goal of the study (Hair et al., 2014, p. 14). Additionally, PLS-SEM makes no assumption about the underlying data and is robust to non-normal data. Hence, PLS-SEM was selected as the statistical method for this particular study.

In PLS-SEM, the term 'indicator' describe individual variables directly measured in the ICEMS survey whereas latent constructs are groupings of these 'indicator' variables (Value, Future Aspirations, etc.). The arrows connect independent to dependent variables, and numbers next to the arrows are path coefficients that correspond to standardized betas in regression analysis (Hair et al., 2014). A SEM has two components, a measurement and structural model. The measurement model suggests how well the individual indicators measured the latent constructs. The structural model suggests how the latent constructs interrelate and how well they predict the outcome construct. Reliability and validity will be presented through a series of criteria (Reliability-Chronbach's alpha and composite reliability; Validity-average variance explained, heterotrait-monotrait ratio). Given the focus of PLS-SEM on prediction over model-testing, overall goodness-of-fit measures are to be used with caution as they are "in their very early stage of research and not fully understood," (SmartPLS, 2015, para. 1), however the standardized root mean square residual (SRMR) is presented to show the overall model fit.

For phase one, final analyses were based on a total sample of 140, just shy of the requirements of 147, given a 5% significance level and desire to detect an $R^2$ of 0.10, for partial least squares structural equation modeling (PLS-SEM; (Hair, Hult, Ringle, & Sarsedt, 2014, p. 21), which was conducted with SmartPLS 3.2.4 (Ringle, Wende, & Becker, 2015). However, this discrepancy may not be as important given the low amount of missing data and the sample size being limited by maximum camp enrollments (Wolf, Harrington, Clark & Miller, 2013).

Next, as directed by Henseler (personal communication, June 12, 2017), the pre- and post- path coefficients were compared using the procedure set forth in Rodriguez-Entrena, Schberth, and Gelhard (2016). In doing so, the pre and post-data is compared and checked for stability as an indicator of equivalence reliability (Gay, Mills, & Airasian, 2009).

<u>Sample, Phase Two</u>

Each of the 163 learner participants in both of the camps had to formally apply for one of the camps (89 in the first camp, 74 in the second camp). The camps accepted students on a first-come, first-serve basis. Of the 163 learners, 46% were female, and the average age was between 11-12 years old. The camps were combined as there were no differences in how students responded on the pre-survey items using an independent samples t-test ($p < 0.001$) after a Bonferroni correction, as t-tests are subject to family-wise error rates (Armstrong, 2014). An important difference between Phase One and Phase Two is the collection of race and ethnicity data for all participants as a part of the application process. Demographic information on the final sample is presented in Table 3. The learners school's title 1 status level was used a proxy for individual socio-economic status (Cowan et al., 2012) and are identified as either not eligible, eligible not participating, targeted, or school-wide (Montana Office of Public Instruction, 2017).

Table 3 Phase two participant demographics

| | 1st Camp | 2nd Camp | Phase Two Total |
|---|---|---|---|
| Total Participants | 85 | 68 | 153 |
| Gender | | | |
| Female | 37 | 34 | 71 |
| Male | 48 | 33 | 81 |
| Other | 0 | 1 | 1 |
| Age | | | |
| 9 | 2 | 0 | 2 |
| 10 | 15 | 2 | 17 |
| 11 | 33 | 18 | 51 |
| 12 | 29 | 19 | 48 |
| 13 | 2 | 24 | 26 |
| 14 | 0 | 3 | 3 |
| Race/Ethnicity | | | |
| White | 74 | 24 | 98 |
| American Indian | 0 | 35 | 35 |

Table 3 Continued

| | | | |
|---|---|---|---|
| Asian | 2 | 2 | 4 |
| Two or More Races | 1 | 3 | 4 |
| Hispanic or Latino | 0 | 4 | 4 |
| Title 1 School Status | | | |
| Not Eligible | 53 | 7 | 60 |
| Eligible, Not Participating | 1 | 3 | 4 |
| Targeted | 21 | 17 | 38 |
| School Wide | 7 | 41 | 48 |
| Not applicable | 3 | 0 | 3 |

Like Phase One of the study, for the first camp, the application process was brief, consisting of one page in which the learner and parent(s) completed contact information and ranked their preferred science sessions. Most importantly, campers paid $429-$644 in tuition to participate in the camp depending on the number of meals and overnight accommodations requested. Of the learners in the first camp, 8% of the learners (N = 85) are enrolled in schools who receive school-wide Title 1 funds, a federal program aimed at providing schools with funds to provide academic support for low-income students (Montana Office of Public Instruction, 2017a, 2017b). By contrast, the learner application process for the completely subsidized second camp was more rigorous, with the same contact information and session rankings, but also a learner letter of intent and two letters of recommendation, one of which had to come from a teacher. Funding for the second camp was made possible via NASA's Northwest Earth and Space Science Pipeline project. Over 63% of the learners in the second camp (N = 68) are enrolled in schools receiving school-wide Title 1 funding (Montana Office of Public Instruction, 2017a, 2017b).

Pre-survey response rates (n=159) were 98%, while post-survey response rates (n=153) were slightly lower (94%). Since six participants did not complete the post-survey, there was a final sample size of 153. In order to generalize to the entire population of 10-14-year-old children in Montana (69,298 people; (Bureau, 2000)), with the confidence level of 95%, the confidence interval is 7.9 (Creative Research Systems, 2012) for Phase One.

Data Collection Strategies, Phase Two.

The self-report survey instrument developed in Phase One is the Informal Cognitive Engagement and Motivation in Science (ICEMS) measure. ICEMS measure was designed to measure middle school learner self-efficacy, value, self-regulation, and cognitive strategy use. Indicators of time, subject, and activity were added to survey items to increase the specificity of the instrument and to fit the informal context (Sinatra et al., 2015). The results from Phase One will be presented in Chapter Four and the discussion presented in Chapter Five will help illuminate areas of strength and weakness of the initial study. However, to contextualize the changes made in the first iteration of the survey, in summary, there were potential shortcomings with the measurement of self-efficacy (low Chronbach's alpha and only two indicators factored into construct), cognitive strategies (low Chronbach's alpha and a lack of questions pertaining to multiple learning strategies), and self-regulation (low Chronbach's alpha and all questions retained were written inversely). 16 questions from the initial iteration of the survey were retained and an additional four questions were added to directly address the potential areas of concern from Phase One. Two of the questions added address self-efficacy: one addresses situational self-efficacy wherein learners compare their abilities with others (Miller et al., 1996), and one that addresses a more generalized self-efficacy phrased in a personal and positive approach (Bandura, 2006; Miller et al., 1996). One question was added to address areas of concern with the construct, cognitive strategies, to look at learner's perception of multiple learning strategies (Miller et al., 1996). Finally, a question was added to understand learner's persistence to the construct, self-regulation (Pintrich & De Groot, 1990). As a result of the analysis completed during Phase One, the ICEMS measure was modified in Phase Two in an attempt to address the potential areas of weakness identified while maintaining the areas with good reliability and validity. As with the first iteration, the full pre- and post-survey items used in Phase Two of the study are provided in Appendix B.

Following Phase One, the structure of the ICEMS measure was implemented in a pre- and post- manner. The pre- and post-surveys contained two questions to link participants with the demographic information collected for the camps and 20 Likert-style questions, asking the learners to rate items on a 5-point scale (1=No, 2=Probably no, 3=Maybe, 4=Probably yes, 5=Yes). The differences between the pre- and post-ICEMS surveys were time scale and verb tense changes. For example, one item on the pre-ICEMS survey read, "I expect to do well on the science activities this week," while the corresponding post-ICEMS survey read, "I did well on the science activities this week."

Following survey development, the ICEMS instrument was administered to the two camps using an online survey program, Qualtrics (Qualtrics, 2015), via mobile devices (Apple, 2012). Importantly, once again, the surveys were administered in a manner to minimize the impact that the evaluation has on the learner's experience in informal contexts (Yoon, Elinich, Wang, Van Schooneveld, & Anderson, 2013). First, the ICEMS survey was brief, containing only 20 questions. Second, the pre-survey was given while learners were checking into the camp and the post-surveys administered during the final lunch prior to learners leaving for the week. The timing of the survey administration ensured that learners did not have to miss aspects of the informal science summer camp.

Data Analysis Strategies, Phase Two.

The data collected for Phase Two of the study was analyzed using correlational analysis, factor analysis, paired sample t-tests, multivariate analysis of variance and linear regression, as set forth in Table 1. First, the data was analyzed for normality and, though it did not meet the assumptions for normality following a Shapiro-Wilks test, the analyses used are robust to violations of the assumption of normality given sufficient sample size (more than 10 observations per variable; Schmidt & Finan, 2017). Next, a correlational analysis was conducted between the survey items, noting areas of high and low correlation to address any issues with either low correlation or multicollinearity. Once evaluated, a factor analysis was conducted on the pre- data from Phase Two to understand the underlying structure of the data. A principle components analysis was conducted using an oblique rotation, Promax, as Phase One results, and the theoretical structure presented suggest that the factors extracted were correlated (Acock, 2016).

Once identified, the factors are aggregated (DiStefano, Zhu, & Mindrila, 2009) and used to explore the pre- and post- informal science experience differences using a paired samples t-test. Also, the individual demographic variables were explored for pre-and post- differences using mulitvariate analysis of variances (MANOVA) and linear regression such that the sociodemographic variables are explored holistically, treated as intersections of a person rather than explored individually.

Given the limitations and delimitations noted in Chapter 1, it is important to note that these findings are subject to issues with reliability and validity which will impact how the results can be interpreted. For example, the sample was obtained using convenience sampling strategy and, as such, the results may not generalize to populations outside of the study context. Additionally, the camps in which the study were conducted are not outlined, nor designed to enhance students cognitive engagment, motivation, and future aspirations in science. The study does not make claims concerning efficacy of particular interventions, rather on the ability of informal contexts to be rich areas to study cognitive engagement, motivation, and future aspirations in science naturally.

# CHAPTER FOUR: RESULTS

Chapter Four was organized by the two Phases conducted as a part of this study and were presented separately, starting with Phase One and followed by Phase Two.

First, an overview of the analytical techniques used will be presented followed by the actual results from the analysis following the order presented in Table 4.

Table 4 Research questions aligned to data analysis techniques

| | Phase 1 | |
|---|---|---|
| Order | Research Question | Data Analysis Technique |
| 1 | What survey questions operationalize cognitive engagement and motivation in science specific to informal contexts for middle school learners? | Correlation, Factor analysis, Partial-least squares structural equation modeling |
| 2 | What impact does informal science experiences have on middle school learner's future aspirations in science? | Paired samples t-test |
| | **Phase 2** | |
| Order | Research Question | Data Analysis Technique |
| 1 | What survey questions operationalize cognitive engagement and motivation in science specific to informal contexts for middle school learners? | Correlation, Factor analysis |
| 2 | What impact does informal science experiences have on middle school learner's future aspirations in science? | Paired samples t-test |
| 3 | As a result of an informal science experience, what is the relationship between middle school learner's cognitive engagement and their gender, race, and socioeconomic statuses? | Multivariate analysis of variance (MANOVA) |
| 4 | As a result of an informal science experience, what is the relationship between middle school learner's value of science and their gender, race, and socioeconomic statuses? | Linear Regression |
| 5 | As a result of an informal science experience, what is the relationship between middle school learner's self-efficacy in science and their gender, race, and socioeconomic statuses? | Linear Regression |

Table 4 Continued

| | | |
|---|---|---|
| 6 | As a result of an informal science experience, what is the relationship between middle school learner's future aspirations in science and their gender, race, and socioeconomic statuses? | Linear Regression |

Results, Phase One.

Descriptive Statistics and Correlational Analysis.

The descriptive statistics and correlations between survey items for Phase One were given in Table 5 and Table 6, respectively. The full survey and survey item abbreviations for Phase One can be found in Appendix A.

Table 5 Descriptive statistics for the survey items used in Phase One

| Survey item | Mean | SD | Skewness | Kurtosis |
|---|---|---|---|---|
| Mistakes | 4.67 | 0.74 | 2.68 | 7.49 |
| PriorKnow | 4.39 | 0.82 | 1.14 | 0.41 |
| DifficultTry | 4.57 | 0.68 | 1.59 | 2.18 |
| DifficultGiveUp* | 1.46 | 0.91 | 2.35 | 5.50 |
| Complete | 4.47 | 0.70 | 1.09 | 0.34 |
| DoWell | 4.34 | 0.84 | 1.09 | 0.35 |
| TryNoSense | 4.73 | 0.57 | 2.25 | 5.01 |
| HighSchool | 4.26 | 0.99 | 1.28 | 1.14 |
| DifficultEasyParts* | 1.58 | 1.13 | 2.09 | 3.39 |
| ExcitedSci | 4.86 | 0.57 | 5.21 | 30.47 |
| Important | 4.55 | 0.83 | 2.11 | 4.67 |
| Challenge | 4.71 | 0.70 | 3.02 | 10.68 |
| Community | 4.41 | 0.86 | 1.82 | 3.98 |
| Interesting | 4.56 | 0.76 | 2.13 | 5.70 |
| College | 3.93 | 1.09 | 0.57 | -0.64 |
| Job | 4.04 | 1.05 | 0.65 | -0.62 |

Note. SD, standard deviation

* Reverse coded

A Shapiro-wilks test of all of the survey items was conducted to test the normality of the survey items (Table 5). All of the tests were significant ($p< 0.05$), therefore, all of these survey items fail to reject the null hypothesis of normality and are considered to have a non-normal distribution. A correlational analysis (Table 6) was conducted prior to a factor analysis to uncover issues with low correlation or multicollinearity. The correlational analysis between the variables show that most of the items are moderately correlated ($r \sim 0.30$) and statistically significant ($p < 0.05$). Inter-item correlations ranged from not statistically significant ($p < 0.05$) to statistically significant ($r = 0.71, p < 0.05$).

Exploratory Factor Analysis

Principal components factor analysis (Table 7) were conducted on the pre-data to guide initial component construction as there is no missing data, and the correlations are moderate (Beavers et al., 2013). The structure was rotated using an orthogonal rotation, Varimax, as there is little empirical evidence to suggest that the factors extracted will be correlated (Acock, 2016). These analyses resulted in the exclusion of nine survey items as a result of issues with cross-loading, such as items loading over 0.50 on multiple factors, and low correlation ($r < 0.20$), creating a more stable factor structure (Table 7). The five component factors identified in the analysis (Value, Future Aspirations, Self-Regulation, Self-Efficacy, and Cognitive Strategies) explained almost 65% of the variance present in the data. Abbreviated names and full survey items are provided in Appendix A.

Table 6 Correlations between survey items

| | Survey item | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Mistakes | 1 | | | | | | | | | | | | | | | |
| 2 | DifficultTry | .22** | 1 | | | | | | | | | | | | | | |
| 3 | DifficultGiveUp* | -0.14 | -.32** | 1 | | | | | | | | | | | | | |
| 4 | Complete | 0.08 | 0.05 | -.22* | 1 | | | | | | | | | | | | |
| 5 | DoWell | 0.07 | .18* | -0.07 | .30** | 1 | | | | | | | | | | | |
| 6 | TryNoSense | 0.16 | .51** | -.24** | .18* | .27** | 1 | | | | | | | | | | |
| 7 | HighSchool | .20* | 0.05 | -0.1 | 0.03 | -0.07 | .24** | 1 | | | | | | | | | |
| 8 | DifficultEasyParts* | -.19* | -.19* | .49** | -.18* | -0.01 | -.28** | -.23** | 1 | | | | | | | | |
| 9 | ExcitedSci | 0.02 | 0.14 | -0.08 | .19* | 0.15 | .36** | .17* | -0.08 | 1 | | | | | | | |
| 10 | Important | 0.07 | 0.15 | -0.12 | 0.12 | 0.07 | .18* | 0.16 | -0.14 | .61** | 1 | | | | | | |
| 11 | Challenge | 0.03 | .28** | -.25** | .19* | .31** | .32** | .17* | -.20* | .65** | .50** | 1 | | | | | |
| 12 | Community | 0.03 | 0.1 | -0.05 | 0.08 | 0.09 | .26** | .25** | -0.09 | .55** | .44** | .43** | 1 | | | | |
| 13 | Interesting | 0.01 | .19* | -.24** | .19* | .18* | .32** | .23** | -.27** | .70** | .48** | .68** | .40** | 1 | | | |
| 14 | College | 0.07 | 0.15 | -0.14 | 0.08 | 0.02 | .22** | .48** | -0.14 | .40** | .44** | .38** | .36** | .37** | 1 | | |
| 15 | Job | 0.11 | .19* | -0.15 | 0.09 | 0.04 | .33** | .38** | -.18* | .44** | .45** | .41** | .37** | .41** | .71** | 1 | |
| 16 | PriorKnow | .19* | .36** | -.23** | 0.09 | 0.13 | .24** | 0.12 | -.24** | .23** | .27** | .30** | .21* | .20* | .26** | .30** | 1 |

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

Table 7 Factor analysis of the survey items in Phase One

| Abbreviation | Value | Cognitive Strategies | Future Aspirations | Self-Regulation | Self-Efficacy |
|---|---|---|---|---|---|
| ExcitedSci | **0.86** | 0.09 | 0.08 | 0.02 | 0.13 |
| Interesting | **0.78** | 0.06 | 0.06 | -0.25 | 0.15 |
| Challenge | **0.77** | 0.22 | 0.01 | -0.16 | 0.20 |
| ImportantSci | **0.73** | 0.10 | 0.16 | -0.05 | -0.05 |
| Community | **0.64** | 0.09 | 0.23 | 0.09 | 0.02 |
| TryFigureOut | 0.10 | **0.85** | -0.04 | -0.15 | 0.01 |
| TryNoSense | 0.24 | **0.61** | 0.19 | -0.12 | 0.27 |
| Prior Know | 0.24 | **0.59** | 0.11 | -0.16 | -0.08 |
| Mistakes | -0.22 | **0.41** | 0.42 | -0.09 | 0.18 |
| High School | 0.11 | 0.01 | **0.81** | -0.12 | 0.00 |
| College | 0.48 | 0.09 | **0.67** | -0.03 | -0.07 |
| Job | 0.51 | 0.19 | **0.60** | -0.03 | -0.06 |
| DifficultEasyParts | -0.07 | -0.14 | -0.18 | **0.82** | -0.05 |
| DifficultGiveUp | -0.09 | -0.24 | 0.01 | **0.81** | -0.06 |
| Complete | 0.11 | -0.12 | 0.08 | -0.28 | **0.77** |
| DoWell | 0.14 | 0.29 | -0.13 | 0.16 | **0.75** |

[1]Extraction Method: Principal Component Analysis
Rotation Method: Varimax with Kaiser Normalization.
Bolded numbers show which indicators loaded onto each factor.

The nine survey items excluded were intended to measure self-efficacy (3 items), self-regulation (3 items), cognitive strategies (2 items) and value (1 item). Items removed from self-efficacy dealt primarily with affective components, leaving only items that measured perceived ability. Items excluded on self-regulation were varied, and measured perceived control, goal setting, and task persistence. Cognitive strategy items excluded from the analysis were questions specific to shallow strategy use, with those two items focusing on strategies for basic memorization (Miller, Greene, Montalvo, Ravindran, & Nichols, 1996). The item removed that initially was designed to measure learners value dealt with overall interest in science. Theoretically, interest in science could be seen as an indicator of affective engagement rather than motivation.

The items that loaded onto the factors were averaged to create aggregated latent constructs (DiStefano et al., 2009). Descriptive statistics and correlations between constructs are presented in Table 8, and show significant small to medium, positive relationships between the components with the exception of self-efficacy which show no significant correlations to self-regulation and future aspirations, evidence of convergent and discriminant validity respectively (Hair et al., 2014).

Table 8. Descriptive statistics and correlations between the latent constructs of Phase One

| | Mean | S.D. | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|---|
| 1 Value | 4.62 | 0.59 | -- | | | | |
| 2 Cognitive Strategies | 4.59 | 0.48 | 0.33** | -- | | | |
| 3 Future Aspirations | 4.08 | 0.86 | 0.52** | 0.33** | -- | | |
| 4 Self-Regulation | 4.48 | 0.88 | 0.22** | 0.39** | 0.22** | -- | |
| 5 Self-Efficacy | 4.41 | 0.62 | 0.24** | 0.24** | 0.05 | 0.16 | -- |

** correlation is statistically significant at the <0.01 level (2-tailed)
Note. S.D., standard deviation

Partial Least-Squares Structural Equation Modeling

Next, PLS-SEM was used explore the interrelationships between the components and future aspiration in science (Figure 6). Figure 6 provides both the measurement model, the relationship between the indicator variables (boxes) and their associated latent constructs (circles), and the structural model, the relationship between the latent constructs (circles). Arrows between the latent constructs are directional, showing independent and dependent relationships. For example, the arrow between value and future aspirations designates value as the independent variable acting on the dependent variable, future aspirations. Numbers along these arrows are path coefficients and show the direct effect between the independent and dependent variables and numbers within parenthesis are the associated *p*-values. In addition, there are indirect effects as relationships between the latent constructs are mediated by each other. Take the relationship between value and future aspirations as an example. The total effect of value on future aspirations was larger than the direct effect of 0.46, as the relationship was mediated by both cognitive strategies and self-regulation, thereby creating indirect effects. Finally, $R^2$ values within the latent constructs show the amount of variance explained by the latent constructs that point at it through the structural model, with significant values ($p < 0.05$) being denoted with an asterisk. Using cognitive strategies to illustrate this, 26% of variance was explained by combination of self-efficacy, value, and self-regulation as all had arrows that pointed towards the latent construct of cognitive strategies. The greater the $R^2$ value, the better the structural model is at predicting the latent constructs (Hair, Sarstedt, Ringle, & Mena, 2012, p. 93).

Measurement Model. The measurement model met most of the minimum requirements for reliability and validity. Beginning with reliability, 12 of the 16 standardized indicator loadings were above the threshold of 0.70 (Hair et al., 2014; Table 3), providing a measure of the indicators' reliability. These four indicators were retained as the corresponding latent constructs present satisfactory levels of reliability and validity and because they were well-supported by the literature (Pintrich & De Groot, 1990) or represent the next phase of the participants education (Glynn et al., 2009).

The latent constructs had Chronbach's alphas between 0.46 and 0.86 (Table 9), with the full scale being 0.62. There were several reasons why self-efficacy, cognitive strategies, and self-regulation constructs might have displayed lower Chronbach's alpha scores. Each of these latent constructs had only a few indicator variables. This is in part due to design in order to keep the total survey questions asked of learners low and, also, as a result of the factor analysis and items either not loading or cross-loading. Therefore, the low Chronbach's alphas could have been potentially attributed to a low number of questions in the initial survey that measure the constructs and/or a low correlation between constructs (Table 8). These alpha values were similar to those found in other scales for cognitive engagement (Greene, 2015; Pintrich, Smith, Garcia, & McKeachie, 1993). Also, "in the context of PLS-SEM, composite reliability is considered a more suitable criterion of reliability" (Hair et al., 2014, p. 115) over Chronbach's's alpha. Chronbach's alpha assumes equal indicator loadings and is better suited to confirmatory studies whereas in this study (Hair et al., 2014), the indicator loadings are not equal, and the intent is to explore cognitive engagement, motivation, and future aspirations in science. As such, all composite reliabilities are greater than the level suggested by Hair et al. (2014) of 0.71.

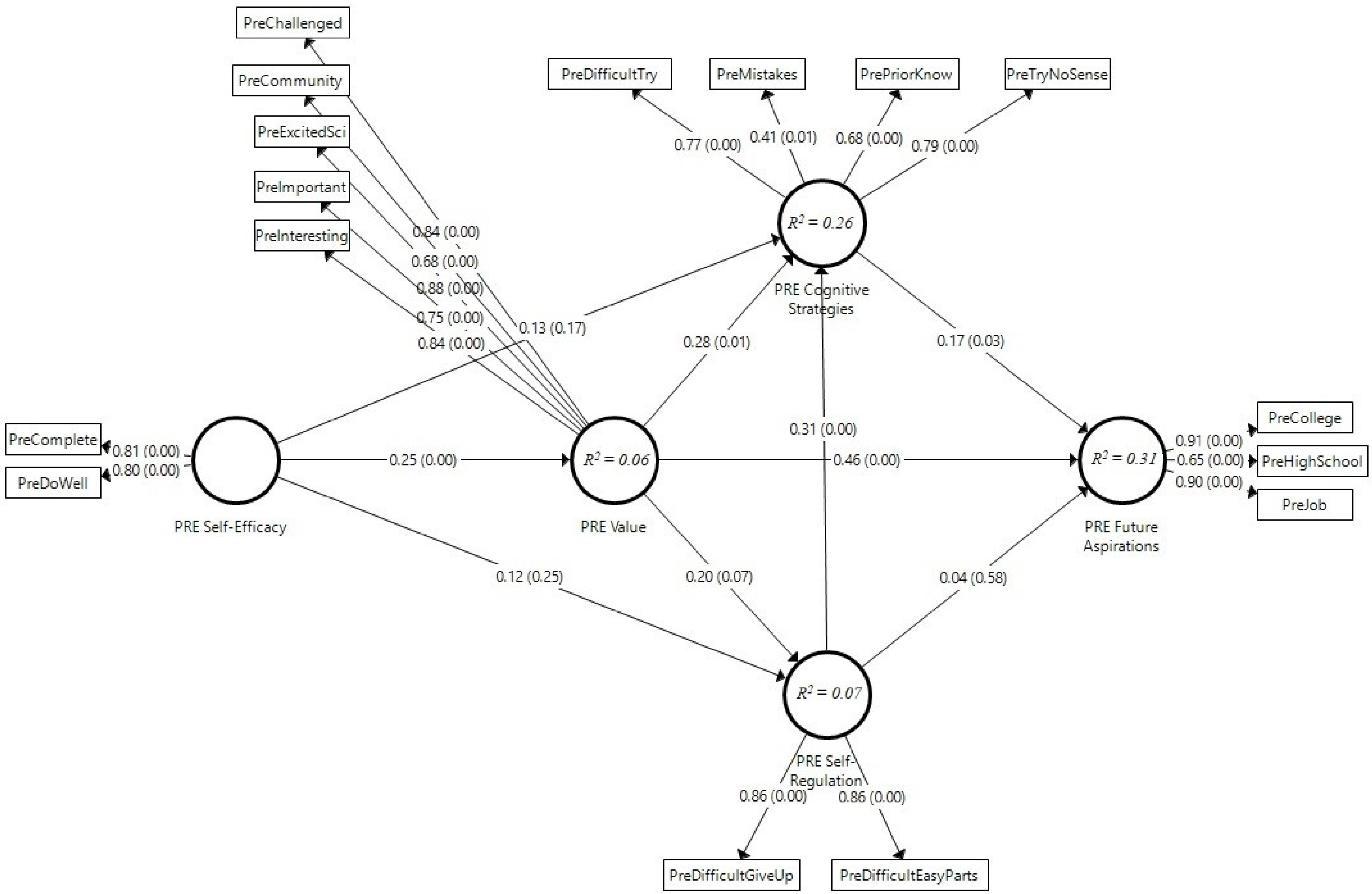

Figure 6. PLS-SEM showing the measurement and structural model, and the percent of variance explained

Therefore, it could be concluded that the measurement model displays acceptable reliability, given the exploratory nature of the study and this approach to structural equation modeling.

Table 9 Measurement model for the PLS-SEM

| Latent Construct | Indicator | S. Loading | C. Alpha | C.R. | AVE |
|---|---|---|---|---|---|
| Value | Challenge | 0.84 | 0.86 | 0.90 | 0.64 |
| | Community | 0.68 | | | |
| | ExcitedSci | 0.88 | | | |
| | Important | 0.75 | | | |
| | Interesting | 0.84 | | | |
| Future Aspirations | College | 0.91 | 0.77 | 0.86 | 0.68 |
| | HighSchool | 0.65 | | | |
| | Job | 0.90 | | | |
| Self- Efficacy | Complete | 0.81 | 0.46 | 0.79 | 0.65 |
| | DoWell | 0.80 | | | |
| Self- Regulation | DifficultEasyParts* | 0.86 | 0.66 | 0.85 | 0.75 |
| | DifficultGiveUp* | 0.86 | | | |
| Cognitive Strategies | DifficultTry | 0.77 | 0.61 | 0.77 | 0.46 |
| | Mistakes | 0.41 | | | |
| | PriorKnow | 0.68 | | | |
| | TryNoSense | 0.79 | | | |

Note: S. Loading, standardized loading; C. Alpha, Cronbach's alpha; C.R., composite reliability; AVE, average variance extracted

*Items were reverse coded

To evaluate convergent validity, the average variance extracted (AVE) values for the latent constructs except cognitive strategies were above the threshold of 0.50 (Table 3; Hair et al., 2014), meaning that the constructs explained close to or over half of the variance of its indicators. Finally, the Heterotrait-Monotrait ratios (HTMT) were considered to measure discriminant validity, a measure aimed at understanding how well a latent construct captures unique aspects of the model. Henseler, Ringle, and Sarstedt

(2015) state a conservative maximum of 0.85 to establish discriminant validity and all constructs had HTMT's below this level, ranging from 0.14 to 0.62.

Structural Model. Hair et al. (2014) set five steps for evaluating structural models (p. 186). First, the collinearity between the latent constructs were analyzed using the variance inflation factor (VIF). Construct VIF values should fall between 0.20 and 5.00 to be retained and all latent constructs included in the PLS-SEM had VIF values between 1.00 and 1.32. Second, the bootstrapping procedure was run with the suggested 5,000 samples and the total effects were calculated. There were moderate, but statistically significant ($p < 0.05$), total effects between self-efficacy, value, and future aspirations (Table 10). Value had the largest total effect on future aspirations (0.54), with moderate to small effects between other latent constructs. Third, statistically significant ($p < 0.05$) $R^2$ values were found in future aspirations in science ($R^2 = 0.31$) and cognitive strategies ($R^2 = 0.26$), but value ($R^2 = 0.06$, $p < 0.1$) and self-regulation were not significant ($R^2 = 0.07$, $p < 0.3$). These were considered weak to moderate values. Fourth, the effect sizes ($f^2$) were calculated and the only significant effect is between value and future aspirations ($f^2 = 0.26$, $p < 0.05$). The $Q^2$ values, a measure of the paths predictive relevance, were all larger than 0, the threshold set by Hair et al. (2014), with the largest being 0.19 on future aspirations.

Fifth and final, although measures of fit were not typically associated with PLS-SEM, to evaluate the overall fit of the model, the standardized root mean square residual (SRMR) level was evaluated. The SRMR level of 0.08 falls below the maximum threshold of 0.10 (SmartPLS, 2015), evidence of an overall reasonable fit of the PLS-SEM.

Table 10 Total effects between latent constructs

| Structural Path | Total Effects | *t* | *p*-Value | 95% Bca Confidence Interval |
|---|---|---|---|---|
| Cognitive Strategies -> Future Aspirations | 0.18 | 4.72 | 0.00 | (0.11,0.26) |
| Cognitive Strategies -> Value | 0.33 | 5.40 | 0.00 | (0.22,0.46) |
| Self-Efficacy -> Cognitive Strategies | 0.34 | 5.65 | 0.00 | (0.20,0.45) |
| Self-Efficacy -> Future Aspirations | 0.17 | 4.71 | 0.00 | (0.08,0.23) |
| Self-Efficacy -> Self-Regulation | 0.24 | 3.65 | 0.00 | (0.09,0.35) |
| Self-Efficacy -> Value | 0.32 | 5.82 | 0.00 | (0.18,0.42) |
| Self-Regulation -> Cognitive Strategies | 0.19 | 2.97 | 0.00 | (0.06,0.29) |
| Self-Regulation -> Future Aspirations | 0.15 | 2.90 | 0.00 | (0.06,0.26) |
| Self-Regulation -> Value | 0.28 | 3.41 | 0.00 | (0.13,0.45) |
| Value -> Future Aspirations | 0.54 | 11.08 | 0.00 | (0.41,0.61) |

**Note. Bca, Bias-corrected and accelerated bootstrap**

Comparison of Pre- and Post-PLS-SEM models

As the factor analysis and the PLS-SEM were based on the pre-survey data, the post- data was explored as a measure of stability and reliability. The post-ICEMS survey data were analyzed using the same structure obtained from the pre-ICEMS factor analysis. Next, a PLS-SEM model was generated using the post-data following the same procedures and structure as the pre-data. Using the model parameter estimates (5,000 bootstrapping samples), the path coefficients from both the pre- and post-models were compared for differences. Once the difference between bootstrap samples for the same paths were calculated, a 95% confidence interval was calculated (Table 11).

Table 11 Confidence interval for the differences between pre-post bootstrapping sample for path coefficients

| Path | 2.50% | 97.50% |
|---|---|---|
| Value -> Self-Regulation | -0.22 | 0.33 |
| Value -> Future Aspirations | -0.15 | 0.31 |
| Value -> Cognitive Strategies | -0.30 | 0.27 |
| Self-Efficacy -> Value | -0.05 | 0.46 |
| Self-Efficacy -> Self-Regulation | -0.43 | 0.07 |
| Self-Efficacy -> Cognitive Strategies | -0.06 | 0.44 |
| Self-Regulation -> Future Aspirations | -0.35 | 0.03 |
| Self-Regulation -> Cognitive Strategies | -0.30 | 0.25 |
| Cognitive Strategies -> Future Aspirations | -0.32 | 0.13 |

As all of the confidence intervals contain zero, there are no statistically significant differences between the pre- and post-path coefficients (Rodriguez-Entrena, Schberth, & Gelhard, 2016, Section 4), evidence of equivalence or stability reliability (Gay et al., 2009).

Pre- and Post- Results from the ICEMS Survey

Using the results from the factor analysis (Table 7), the loaded factors were summed to create aggregated factors for both the pre- and post-survey data (DiStefano et al., 2009) as the study was exploratory in nature. As the latent constructs had significant results on a Shapiro-Wilk test of normality ($p < 0.00$), Related samples Wilcoxon signed ranked tests were conducted to better understand the impacts of the informal science summer camp experience on learner cognitive engagement, motivation, and future aspirations in science (Table 12) through the component factors. Data was obtained from the ICEMS survey, given pre- and post- camp.

Table 12 Descriptive statistics and Wilcoxon signed-rank tests

| | Pre (N=140) | | Post (N=140) | | Wilcoxon signed ranked test | |
|---|---|---|---|---|---|---|
| **Construct** | ***M*** | ***SD*** | ***M*** | ***SD*** | ***Z*** | ***p- value*** |
| **Future Aspirations** | **4.08** | **0.86** | **4.31** | **0.88** | **3.55** | **0.00** |
| **Value** | **4.62** | **0.59** | **4.71** | **0.44** | **1.79** | **0.07** |
| **Self-Efficacy** | **4.41** | **0.62** | **4.61** | **0.60** | **3.30** | **0.001** |
| **Self-Regulation** | **4.48** | **0.88** | **4.32** | **1.10** | **2.10** | **0.04** |
| **Cognitive Strategies** | **4.59** | **0.48** | **4.73** | **0.43** | **3.50** | **0.00** |

**Note: M, mean; SD, standard deviation**

As Wilcoxon signed-rank tests are subject to family-wise error rates, the Bonferroni correction (Armstrong, 2014) was used to adjust the threshold *alpha* probability value of 0.05, to a threshold significance was $p < 0.008$. Significant difference between pre-and post-scores on the ICEMS survey were found with future aspirations ($Z = 3.55$, $p < 0.00$), self-efficacy ($Z = 3.30$, $p < 0.001$), and cognitive strategies ($Z = 3.50$, $p < 0.001$). Despite the gain between the pre- and post-scores on value, there was not a statistically significant increase. Self-regulation dropped between the pre- and post-surveys, though this decrease was also not statistically significant.

## Summary, Phase One

In Phase One, correlational and factor analysis of the pre-survey data guided component construction to explore cognitive engagement (cognitive strategies and self-regulation), motivation (value and self-efficacy), and future science aspirations in informal science contexts. The theoretical relationship between these constructs was investigated using a partial-least square structural equation model. Results reveal that the latent constructs measuring cognitive engagement (cognitive strategies and self-regulation) and motivation (value and self-efficacy) significantly predict future aspirations in science ($R^2 = 0.31$, $p < 0.05$). Furthermore, given by the total effects (Table 11), all but self-regulation significantly predicts future aspirations in science with the motivational construct of value having the largest total effect of 0.52. Overall, the model shows acceptable levels of fit (SRMR >0.1; SmartPLS, 2015).

In seeking to understand the impact of the informal science experience through a comparison of the pre-and post-survey data, paired samples t-tests were conducted on the aggregated latent constructs (value, self-efficacy, cognitive strategies, and self-regulation). Participants rated themselves significantly higher in self-efficacy, cognitive strategies, and future aspirations in science in the post-survey ($p < 0.008$). These statistically significant results, along with the effect sizes, suggest small to moderate gains as a result of the informal science summer camp experience.

## Results, Phase Two

### Descriptive Statistics and Correlational Analysis

The descriptive statistics and correlations between survey items (N = 142) for Phase Two are given in Table 13 and Table 14, respectively. The full survey questions and the survey item abbreviations for Phase Two can be found in Appendix B.

Table 13 Descriptive statistics for Phase Two survey items

| Item | Mean | SD | Skewness | Kurtosis |
|---|---|---|---|---|
| Complete | 4.15 | 0.92 | 1.09 | 0.98 |
| DifficultMoveOn[1] | 1.63 | 1.09 | -1.76 | 2.19 |
| Dowell | 4.03 | 0.94 | 0.89 | 0.69 |
| Trynosense | 4.77 | 0.55 | 3.30 | 15.08 |
| Highschool | 4.09 | 1.06 | 0.94 | 0.17 |
| Goodstrategies | 4.35 | 0.79 | 1.12 | 1.24 |
| College | 3.77 | 1.10 | 0.35 | -0.86 |
| Hardeasy[1] | 1.65 | 1.14 | -1.78 | 2.18 |
| Important | 4.38 | 0.86 | 1.63 | 3.18 |
| Workhard | 4.57 | 0.78 | 1.91 | 2.97 |
| Canlearn | 4.58 | 0.69 | 1.86 | 4.44 |
| Community | 4.30 | 0.82 | 1.13 | 1.19 |
| Interesting | 4.46 | 0.80 | 1.52 | 2.12 |
| DifficultFigureOut | 4.58 | 0.63 | 1.25 | 0.40 |
| Job | 4.01 | 1.05 | 0.69 | -0.37 |

**Note. SD, standard deviation**
**[1] items are reverse**

A Shapiro-wilks test of all of the survey items was conducted to test the normality of the survey items (Table 13). All of the tests were significant ($p< 0.05$), therefore, all of these survey items fail to reject the null hypothesis of normality and are considered to have a non-normal distribution.

A correlational analysis between the variables revealed that most of the items were moderately correlated (Table 14; ~0.30) and statistically significant ($p < 0.05$). Inter-item correlations ranged from 0.55 to not statistically significant (Table 14; $p < 0.05$).

Table 14 Correlations between survey items in Phase Two

| | Item | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Complete | 1.00 | | | | | | | | | | | | | | |
| 2 | DifficultMoveOn[1] | -0.12 | 1.00 | | | | | | | | | | | | | |
| 3 | Dowell | 0.40* | -0.06 | 1.00 | | | | | | | | | | | | |
| 4 | Trynosense | 0.22* | -0.18* | 0.18* | 1.00 | | | | | | | | | | | |
| 5 | Highschool | 0.30* | -0.17* | 0.31* | 0.25* | 1.00 | | | | | | | | | | |
| 6 | Goodstrategies | 0.34* | -0.06 | 0.33* | 0.36* | 0.29* | 1.00 | | | | | | | | | |
| 7 | College | 0.29* | -0.16 | 0.38* | 0.33* | 0.49* | 0.30* | 1.00 | | | | | | | | |
| 8 | Hardeasy[1] | -0.17* | 0.35* | -0.16 | -0.23 | -0.26 | -0.28 | -0.27 | 1.00 | | | | | | | |
| 9 | Important | 0.37* | -0.14 | 0.30* | 0.19* | 0.36* | 0.36* | 0.50* | -0.27 | 1.00 | | | | | | |
| 10 | Workhard | 0.35* | -0.27* | 0.29* | 0.49* | 0.50* | 0.44* | 0.49* | -0.49 | 0.48* | 1.00 | | | | | |
| 11 | Canlearn | 0.46* | -0.21* | 0.34* | 0.19* | 0.35* | 0.34* | 0.26* | -0.25 | 0.44* | 0.44* | 1.00 | | | | |
| 12 | Community | 0.33* | -0.04 | 0.21* | 0.21* | 0.26* | 0.25* | 0.32* | -0.16 | 0.39* | 0.21* | 0.32* | 1.00 | | | |
| 13 | Interesting | 0.31* | -0.12 | 0.17* | 0.34* | 0.28* | 0.38* | 0.29* | -0.40 | 0.44* | 0.42* | 0.37* | 0.34* | 1.00 | | |
| 14 | DifficultFigureOut[1] | 0.36* | -0.30 | 0.28* | 0.35* | 0.45* | 0.39* | 0.37* | -0.48 | 0.35* | 0.55* | 0.39* | 0.28* | 0.35* | 1.00 | |
| 15 | Job | 0.28* | 0.01 | 0.32* | 0.30* | 0.38* | 0.36* | 0.66* | -0.19 | 0.52* | 0.36* | 0.29* | 0.40* | 0.24* | 0.39* | 1.00 |

• significant at p<0.05

[1] Item is reverse coded

Exploratory Factor Analysis

Principal components factor analysis (Table 15) were conducted on the pre-data to guide initial component construction as there is no missing data, and the correlations are moderate (Beavers et al., 2013). The structure was rotated using an oblique rotation, Promax, as Phase One results, and the theoretical structure presented suggest that the factors extracted will be correlated (Acock, 2016).

These analyses resulted in the exclusion of five survey items as a result of issues with cross-loading, such as items not loading higher than 0.4 or loading over 0.5 on multiple factors, creating a more stable factor structure (Table 1). Items were also excluded as a result of the theoretical framework. For example, one of the items dropped (ExcitedSci) intended to measure value, loaded on multiple factors over 0.5 (Future Aspirations and Self-Regulation), yet the other items in these factors were not related theoretically to ExcitedSci. Therefore, in addition to being cross-loaded, it was dropped as it did not make theoretical sense to maintain the item.

The five items excluded in the second iteration of the ICEMS survey were intended to measure cognitive strategies (2 items), self-regulation (1 item), self-efficacy (1 item) and value (1 item). The two items removed from cognitive strategies were included in Phase One of the study and were intended to measure a willingness to learn from mistakes (Mistakes; Pintrich & DeGroot, 1990) and how prior knowledge impacts the learning process (PriorKnow; Pintrich & DeGroot, 1990). In Phase One of the study, both “Mistakes” and “PriorKnow” loaded below a 0.70 level onto Cognitive Strategies (see Table 9; Standardized loadings of the PLS-SEM) and these items failed to factor without cross-loading onto multiple factors. Though these items are well based in the literature, as a result of both Phase One and Phase Two, these items were dropped from the survey. Additionally, the one item dropped that was intended to measure self-regulation from the Pintrich and De Groot (1990) survey as it was heavily cross-loaded. Following Miller et al. (1996)'s work, an item was included that looked at a learner's self-efficacy in comparison to others. The item was cross-loaded and, therefore, removed.

In the model, five components identified in the factor analysis (Value, Future Aspirations, Self-Regulation, Self-Efficacy, and Cognitive Strategies) explain almost 67% of the variance present in the data, see Table 15 for factor loadings. Abbreviated names and full survey items are provided in Appendix B.

Table 15 Factor analysis for the Phase Two survey items

| Variable | Future Aspirations | Self-Efficacy | Cognitive Strategies | Value | Self-Regulation |
|---|---|---|---|---|---|
| College | **0.87** | -0.04 | 0.04 | -0.01 | -0.06 |
| Job | **0.85** | -0.06 | 0.05 | 0.20 | 0.19 |
| Highschool | **0.50** | 0.19 | 0.04 | -0.09 | -0.25 |
| Dowell | 0.18 | **0.80** | 0.04 | -0.25 | 0.11 |
| Complete | -0.13 | **0.76** | 0.02 | 0.21 | 0.03 |
| Canlearn | -0.13 | **0.60** | -0.10 | 0.37 | -0.21 |
| Trynosense | 0.09 | -0.11 | **0.86** | -0.06 | 0.05 |
| Goodstrategies | -0.06 | 0.31 | **0.67** | 0.12 | 0.21 |
| Workhard | 0.20 | 0.09 | **0.45** | 0.02 | -0.35 |
| Community | 0.29 | 0.01 | -0.13 | **0.73** | 0.15 |
| Interesting | -0.14 | -0.08 | 0.40 | **0.66** | -0.07 |
| Important | 0.44 | 0.08 | -0.12 | **0.53** | -0.06 |
| DifficultGiveUp[1] | 0.07 | 0.00 | 0.21 | 0.11 | **0.93** |
| DifficultEasyParts[1] | 0.03 | 0.16 | -0.22 | -0.17 | **0.65** |
| DifficultFigureOut | 0.16 | 0.15 | 0.25 | 0.04 | **-0.44** |

[1]Extraction Method: Principal Component Factor Analysis, Rotation Method: Varimax with Kaiser Normalization.

*Items were reverse coded

Note. Bolded numbers show which indicators loaded onto each factor

The factors identified in the factor analysis guided the construction of the pre and post measures of Value, Future Aspirations, Self-Regulation, Self-Efficacy, and Cognitive Strategies. The survey items that factored into these constructs were averaged to created overall measures following a sum scores methods adhering to the cut-off points described in the factor analysis presented above (DiStefano et al., 2009: Table 15).

Table 16 Descriptive statistics and correlations between Phase Two latent factors

| Descriptive statistics | | | Correlations | | | | |
|---|---|---|---|---|---|---|---|
| Factors | Mean | SD | 1 | 2 | 3 | 4 | 5 |
| 1 Future Aspirations | 2.96 | 0.88 | 1 | | | | |
| 2 Self-Efficacy | 3.25 | 0.66 | 0.49 | 1 | | | |
| 3 Cognitive Strategies | 3.56 | 0.56 | 0.56 | 0.50 | 1 | | |
| 4 Value | 3.38 | 0.64 | 0.56 | 0.52 | 0.53 | 1 | |
| 5 Self-Regulation | 3.43 | 0.73 | 0.36 | 0.33 | 0.49 | 0.37 | 1 |

**Note. SD, standard deviation**

In order to assess reliability and validity of the updated ICEMS survey, Chronbach's alpha, item-rest correlations and interitem correlations were conducted on the aggregated factors measuring cognitive engagement, motivation, and future aspirations in science. Chronbach's alphas were generated to look at the internal consistency of the latent constructs (Table 17). In addition, the item-rest and inter-item correlations were also calculated to show how well the latent constructs relate to the rest of the model as a whole (item-rest correlation) and how the latent constructs correlate to each other with the removal of the factor (interitem correlation), both are measures of criterion-related validity. As seen in Table 17, all of the Chronbach's alphas were considered adequate to good (above 0.7), and the correlations of the items to the latent constructs were all significant ($p < 0.05$) and mostly strong (above $r < 0.5$) (Acock, 2016). The item-rest correlations and inter-item correlations all indicate a strong and positive relationship to the rest of the model, which suggested good convergent validity of the latent constructs (Acock, 2016). Additionally, as these constructs were moderately correlated, the factors likely explain unique variance within the dataset, adding credibility to the constructs discriminant validity.

Table 17 Reliability criteria for Phase Two

| Latent Construct | Indicator | Chronbach's Alpha | item-rest correlation | Interitem Correlation |
|---|---|---|---|---|
| Future Aspirations | College<br>HighSchool<br>Job | 0.77 | 0.64 | 0.45 |
| Value | Community<br>Important<br>Interesting | 0.77 | 0.64 | 0.45 |
| Self- Efficacy | Complete<br>Canlearn<br>DoWell | 0.78 | 0.59 | 0.48 |
| Self- Regulation | DifficultGiveUp[1]<br>DifficultEasyParts[1]<br>DifficultTry | 0.82 | 0.48 | 0.52 |
| Cognitive Strategies | Goodstrategies<br>Workhard<br>TryNoSense | 0.76 | 0.68 | 0.44 |

Note: C. Alpha, Cronbach's alpha; IR Corr, item-rest correlation
[1]Items were reverse coded

Pre- and Post- Results from the ICEMS Survey

Next, using the pre- and post- measures created as a result of the factor analysis and because of the non-normal data distribution, Wilcoxon signed-rank tests were conducted. These tests discerned any significant differences in cognitive engagement, motivation and future aspirations in science between the pre- and post-surveys for all participants in the experience.

Table 18 Descriptive statistics and Wilcoxon sign-rank tests

| | Pre (N=142) | | Post (N=142) | | Wilcoxon signed-rank test | |
|---|---|---|---|---|---|---|
| **Construct** | ***M*** | ***SD*** | ***M*** | ***SD*** | ***Z*** | ***p-value*** |
| **Future Aspirations** | 2.96 | 0.88 | 3.30 | 0.95 | 4.83 | 0.00 |
| **Value** | 3.38 | 0.64 | 3.51 | 0.58 | 3.02 | 0.00 |
| **Self- Efficacy** | 3.25 | 0.66 | 3.60 | 0.56 | 6.22 | 0.00 |
| **Self- Regulation** | 3.43 | 0.73 | 3.30 | 0.90 | 1.55 | 0.12 |
| **Cognitive Strategies** | 3.56 | 0.56 | 3.70 | 0.49 | 2.78 | 0.01 |

**Note. M, mean; SD, standard deviation**

Using the Bonferroni correction (Armstrong, 2014) to a threshold *alpha* probability value of 0.05, the adjusted $p$-value for significance is $p < 0.01$. Significant difference between pre-and post-scores on the ICEMS survey are found with value ($z = 3.02$, $p < 0.00$), self-efficacy ($z = 6.02$, $p < 0.00$), cognitive strategies ($z = 2.78$, $p = 0.01$), and future aspirations ($z = 4.83$, $p < 0.00$). Self-regulation dropped between the pre- and post-surveys ($z = 1.55$, $p = 0.12$), though this decrease was not statistically significant.

Assessing Impacts of the Informal Science Experience

In order to ascertain the impact of the informal science experience on learner's cognitive engagement, motivation, and future aspirations, the aggregated factor scores were used. To assess growth occurring during the informal science experience, the pre-survey aggregate factor scores were subtracted from the post-survey aggregate factor scores. These differences were then explored to understand if the informal science experience differentially impacted learners based on sociodemographic indicators (gender, race, and socioeconomic status).

To begin, using SPSS ("Statistical package for the social sciences," 2016) the descriptive statistics and correlations for the difference scores of value, self-efficacy, cognitive strategies, and self-regulation are given in Table 19.

Table 19. Descriptive statistics and correlations

| | Descriptive Statistics | | | | Correlation | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Mean** | **SD** | **Skewness** | **Kurtosis** | **1** | **2** | **3** | **4** | **5** |
| **1 Diff Self-efficacy** | **0.35** | **0.61** | **0.23** | **3.42** | **–** | | | | |
| **2 Diff Cognitive Strat.** | **0.14** | **0.61** | **-0.85** | **7.16** | **0.32*** | **–** | | | |
| **3 Diff Value** | **0.13** | **0.54** | **0.13** | **4.31** | **0.13** | **0.29*** | **–** | | |
| **4 Diff Future Asp.** | **0.34** | **0.78** | **-0.20** | **4.20** | **0.26*** | **0.27*** | **0.18*** | **–** | |
| **5 Diff Self-Regulation** | **-0.13** | **0.84** | **0.26** | **5.26** | **0.27*** | **0.24*** | **-0.02** | **0.09** | **–** |

**Note. SD, standard deviation**

The factors that measure the growth in cognitive engagement (Diff cognitive strategies and Diff self-regulation) are significantly correlated, therefore, they were examined together. However, the factors intended to measure the growth in motivation (Diff value and Diff self-efficacy) were not correlated, therefore, they will be evaluated separately.

The sociodemographic indicators being explored were gender, race, and socioeconomic status through a learner's school's Title 1 status. Learners identified themselves as either male (coded as 1), female (coded as 2) or other. As only one learner identified as other, they were dropped from the sample. Learners indicated their race as white (coded as 1), Native American, Asian, Hispanic or Latino, or two or more races (all together coded as 2). As several of the racial categories had single responses, the categories were collapsed to white (coded as 1), and learners of color (coded as 2). Learners also wrote down the school that they attended, and their school's title 1 status level was used a proxy for individual socio-economic status (Cowan et al., 2012). There are four levels of Title 1 status identified as either not eligible, eligible not participating, targeted, or school-wide (Montana Office of Public Instruction, 2017). As only four learners came from schools identified as being eligible, but no participating in Title 1 funding, these students were aggregated with those from schools that are targeted. Those who were from schools not eligible were coded as 1, targeted were coded as 2, and school wide were coded as 3.

Differences in Cognitive Engagement. A three-way multivariate analysis of variance (MANOVA) was conducted to determine the effects of gender (male, female), race (white, learners of color), and Title 1 status (not eligible, targeted, school wide) on the two dependent variables measuring cognitive engagement (cognitive strategies, self-regulation). Box's test of equality of covariance matrices was significant ($M = 158.23$, $F$ $(30, 1252) = 4.37$, $p < 0.00$), which violates one of the assumptions of the test, but it considered "overly sensitive… in the sense that it detects heterogeneity so minor as to have inconsequential effects on the MANOVA test" (Olson, 1974, p. 906). As such the MANOVA was conducted, but to address the potential issues with the homogeneity assumption the results was reported using Pillai's trace, as it was considered more robust, particularly with small groups and high levels of kurtosis (Olson, 1974, p. 906-907), which described the differences scores.

Significant differences in cognitive strategy growth were found among learners of different gender (Pillai's trace = 0.06, $F$ $(2, 129) = 4.46$, $p < 0.01$, $\eta^2 = 0.06$) and Title 1 status (Pillai's trace = 0.12, $F$ $(4, 258) = 4.22$, $p < 0.00$, $\eta^2 = 0.06$). However, two significant interaction effects were also detected between a learner's race and Title 1 status (Pillai's trace = 0.09, $F$ $(4, 260) = 3.21$, $p < 0.01$, partial $\eta^2 = 0.05$), and race and gender (Pillai's trace = 0.07, $F$ (2, 129) = 4.81, $p < 0.01$, partial $\eta^2 = 0.07$) on their growth in cognitive strategies, preventing a clear interpretation of the main effects.

A univariate analysis for a learner's race by Title 1 status interaction effect estimated that learners of color who attended schools not eligible for Title 1 funding (estimated M = 0.83, SE = 0.25) averaged higher gains in cognitive strategies as a result of the informal science experience than white learners (estimated M= 0.01, SE = 0.09), $F$ (1, 136) = 8.01, $p < 0.00$). No differences were found between white and learners of color who attended schools receiving Targeted and School-wide Title 1 funding.

A univariate analysis for a student's race by gender interaction effect estimated that male learners of color (estimated M = 0.01, SE = 0.12) did not significantly differ from female learners of color (estimated M= 0.37, SE = 0.14) on their growth in cognitive strategies as a result of the informal science experience, ($F$ (1, 138) = 3.80, $p = 0.053$). No differences were found between males or females who identify as white.

<u>Differences in Value of Science</u>. A linear regression was conducted to evaluate how well a learner's sociodemographic intersections (gender, race, Title 1 status), predicted how much an informal science experience impacted their value of science. The learner's value of science as a result of the informal science experience was calculated by subtracting the pre-aggregated survey scores from the post-aggregated survey schools for value, identified in the factor analysis (Table 20).

The bivariate correlations between the three independent variables and the growth of value were small but significant (Table 20; $p < 0.05$). The coding structure is as follows: gender (male-0, female-1), race (white-0, learners of color-1), and Title 1 status (not eligible-0, targeted-1, school wide-2). In the sample, 52.8% identified as male, 67.6% identified as white, 38% attended schools that did not qualify for Title 1 funds, 28.2% attended schools with targeted assistance, and 33.8% attended schools receiving school-wide Title 1 funds.

Table 20 Correlations between the differences in value and demographic indicators

| | | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|
| 1 | Diff Value | 1 | | | | | |
| 2 | Gender | 0.21* | 1 | | | | |
| 3 | Race | 0.19* | 0.05 | 1 | | | |
| 4 | Eligible | -0.12 | 0.04 | 0.36* | 1 | | |
| 5 | Targeted | -0.02 | -0.004 | 0.23* | 0.49* | 1 | |
| 6 | Schoolwide | 0.14* | -0.04 | -0.59* | 0.56* | -0.45* | 1 |

* p<0.05

A linear combination of the three sociodemographic variables were found to be significantly related to the growth in value of science as a result of an informal science experience, $F$ (4,137) = 3.19, $p < 0.01$, $R^2 = 0.09$. The results indicate that only 9% of the variance in how much learners gained in value of science could be accounted for by the linear combination of the sociodemographic indicators. Results from the regression analysis were reported in Table 21. The unstandardized regression coefficients for gender (B = 0.24, $p < 0.01$) was the only significant predictor of growth in the value of science, with males being the reference group. These results indicated that females (coded as 1) see 0.24 increased in their growth in the value of science.

Table 21 Summary of the regression analysis for variables predicting growth in value of science as a result of an informal science experience

| Variable | Unstandardized B | Standardized B | *t* | *p* |
|---|---|---|---|---|
| Gender | 0.24 | 0.22 | 2.68 | 0.01 |
| Race | 0.20 | 0.17 | 1.68 | 0.10 |
| Title 1, Targeted | 0.05 | 0.04 | 0.46 | 0.65 |
| Title 1, School Wide | 0.06 | 0.05 | 0.50 | 0.62 |

Evaluating the assumptions of regression, the bivariate correlations between the variables were significant but low suggesting no issues with multicollinearity. Additionally, plots of the residuals suggested a normal distribution (Figure 7.). Finally, one case had a studentized residual above the threshold of 3 (Pituch & Stevens, 2016; Williams, 2016), though it was retained as the leverage value is 0.018 and the cooks distance is 0.048. All other cases had Cook's distances below 0.072, which falls short of the threshold suggested by Pituch & Stevens (2016) of 1, and leverage values below 0.057, which falls right at the threshold calculated by $3k/n$, or 0.063 (Pituch & Stevens, 2016).

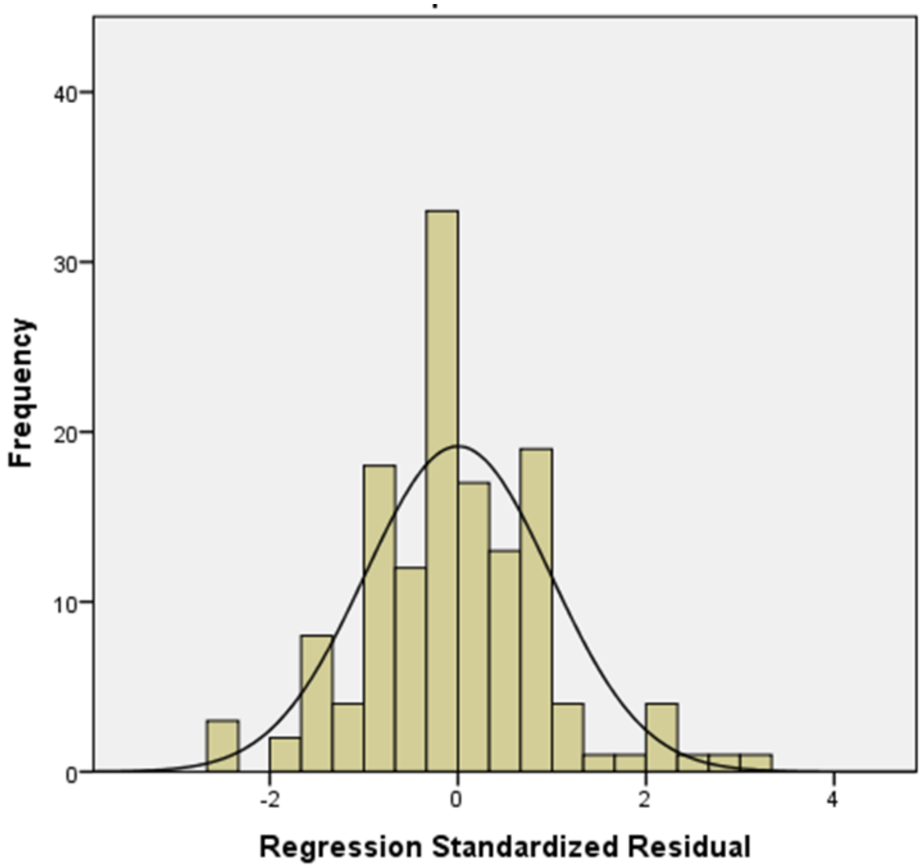


Figure 7. Histogram of the residuals from the linear regression of gender, race, and Title 1 status on student's growth in value of science

Differences in Self-Efficacy in Science. A linear regression was conducted to evaluate how well a learner's sociodemographic intersections (gender, race, Title 1 status), would predict how much an informal science experience impacted their self-efficacy. The learner's self-efficacy in science as a result of the informal science experience was calculated by subtracting the pre-aggregated survey scores from the post-aggregated survey schools for self-efficacy, identified in the factor analysis (Table 15). The bivariate correlations between the three independent variables and the growth of self-efficacy were small (Table 22, $p < 0.05$) or not statistically significant. The coding structure is as follows: gender (male-0, female-1), race (white-0, learners of color-1), and

Title 1 status (not eligible-0, targeted-1, school wide-2). In the sample, 52.8% identified as male, 67.6% identified as white, 38% attended schools that did not qualify for Title 1 funds, 28.2% attended schools with targeted assistance, and 33.8% attended schools receiving school-wide Title 1 funds.

Table 22. Correlations between the difference in self-efficacy and demographic indicators

| | | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|
| 1 | Diff Self-Efficacy | 1 | | | | | |
| 2 | Race | -0.04 | 1 | | | | |
| 3 | gender | 0.11 | 0.05 | 1 | | | |
| 4 | Eligible | 0.19* | 0.36* | 0.04 | 1 | | |
| 5 | Targeted | -0.1 | 0.23* | -0.004 | 0.49* | 1 | |
| 6 | School Wide | -0.09 | -0.59* | -0.04 | 0.56* | 0.45* | 1 |

* p<0.05

A linear combination of the three sociodemographic variables were found to not be significantly related to the growth in self-efficacy in science as a result of an informal science experience, $F$ (4,137) = 1.78, $p$ = 0.14, $R^2$ = 0.05.

Table 23. Summary of the regression analysis for variables predicting growth in science self-efficacy as a result of an informal science experience

| Variable | Unstandardized B | Standardized B | $t$ | $p$ |
|---|---|---|---|---|
| Gender | 0.05 | 0.12 | 1.41 | 0.16 |
| Race | 0.14 | 0.04 | 0.38 | 0.71 |
| Title 1, Targeted | -0.25 | -0.19 | -2.00 | 0.05 |
| Title 1, School Wide | -0.26 | -0.21 | -1.82 | 0.07 |

Evaluating the assumptions of regression, the bivariate correlations between the variables are significant but low suggesting no issues with multicollinearity. Additionally, plots of the residuals suggest a normal distribution (Figure 8). Finally, one case had a studentized residual above the threshold of 3 (Pituch & Stevens, 2016; Williams, 2016), though it was retained as the leverage value is 0.057 (lower than threshold of 0.063) and the cooks distance is 0.15 (lower than threshold of 1; Pituch & Stevens, 2016). All other cases had Cook's distances below 0.08, and leverage values below 0.065.

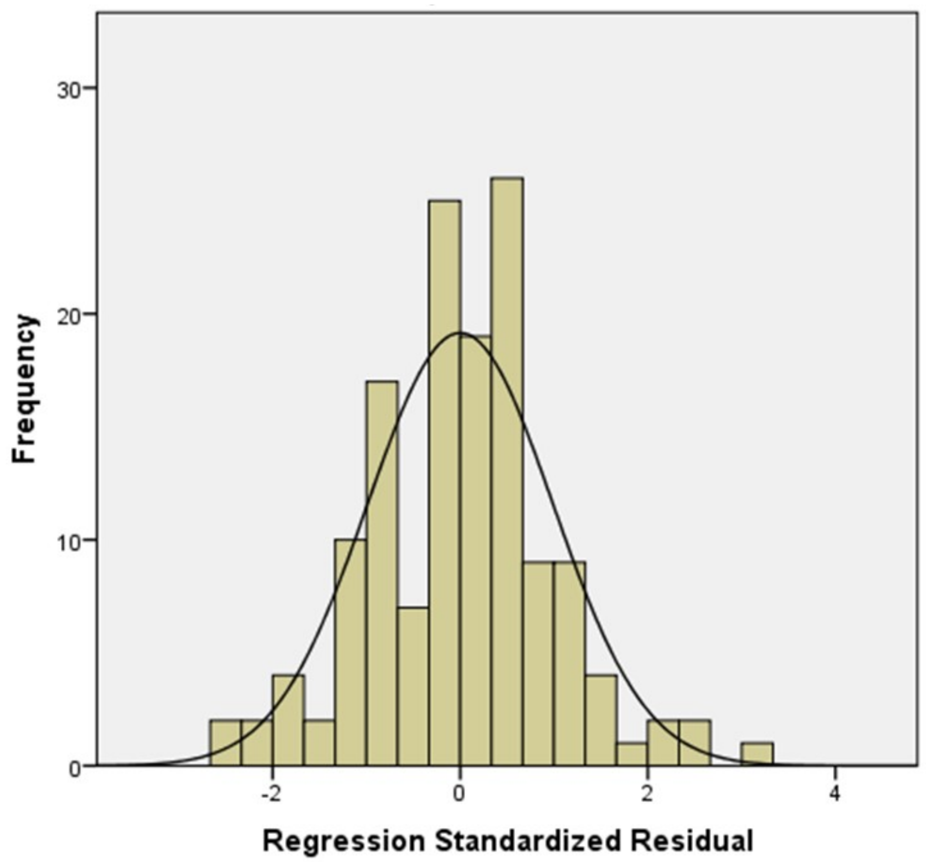


Figure 8 Histogram of the residuals from the linear regression of gender, race, and Title 1 status on student's growth in self-efficacy in science

Results from the regression analysis were reported in Table 23. The significant coefficient with Targeted Title 1 status, may point to issues with interaction effects, as seen in the MANOVA results. Though the regression model was not significant, a one-way analysis of variance test was conducted to ascertain any differences between Title 1 status and the growth in self-efficacy during the informal science summer camp, descriptive statistics are given in Table 24. Results did not reveal any significant differences between the various Title 1 statuses ($F$ (2, 139) = 2.54, $p$ = 0.08).

Table 24 Descriptive statistics for the growth of self-efficacy by student's school's Title 1

| Title 1 Status | Mean | SD |
|---|---|---|
| Not Eligible | 0.49 | 0.53 |
| Targeted | 0.25 | 0.65 |
| School Wide | 0.27 | 0.63 |

**Note. SD, standard deviation**

<u>Differences in Future Aspirations in Science</u>. The learner's future aspirations in science as a result of the informal science experience was calculated by subtracting the pre-aggregated survey scores from the post-aggregated survey schools for future aspirations, identified in the factor analysis (Table 15). Descriptive statistics for the difference between the pre-and post- future aspirations in science was given in Table 25.

Table 25. Descriptive statistics of the difference between pre-and post-future aspirations in science

| Construct | Mean | SD | Skewness | Kurtosis |
|---|---|---|---|---|
| Diff, Future Asp | 0.34 | 0.78 | -0.21 | 1.29 |

**Note. SD, standard deviation**

A linear regression was conducted to evaluate how well a learner's sociodemographic intersections (gender, race, Title 1 status), would predict how much an informal science experience impacted their future aspirations in science. The bivariate correlations between the three independent variables and the growth of value were not statistically significant (Table 26: $p > 0.05$). The coding structure is as follows: gender (male-0, female-1), race (white-0, learners of color-1), and Title 1 status (not eligible-0, targeted-1, school wide-2). In the sample, 52.8% identified as male, 67.6% identified as white, 38% attended schools that did not qualify for Title 1 funds, 28.2% attended schools with targeted assistance, and 33.8% attended schools receiving school-wide Title 1 funds.

Table 26. Correlations between the difference in future aspirations and demographic indicators

| | | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|
| 1 | Diff Future Asp. | 1 | | | | | |
| 2 | Race | -0.02 | 1 | | | | |
| 3 | gender | 0.06 | 0.05 | 1 | | | |
| 4 | Eligible | 0.06 | 0.36* | 0.04 | 1 | | |
| 5 | Targeted | -0.06 | 0.23* | -0.004 | 0.49* | 1 | |
| 6 | School Wide | -0.002 | -0.59* | -0.04 | 0.56* | 0.45* | 1 |

* p<0.05

A linear combination of the three sociodemographic variables were found to not be significantly related to the growth in future aspirations in science as a result of an informal science experience, $F$ (4,137) = 0.32, $p = 0.86$, $R^2 = 0.009$. Results from the regression analysis were reported in Table 27.

Table 27 Summary of the regression analysis for variables predicting growth in future aspirations in science as a result of an informal science experience

| Variable | Unstandardized B | Standardized B | *t* | *p* |
|---|---|---|---|---|
| Gender | 0.10 | 0.07 | 0.76 | 0.45 |
| Race | -0.02 | -0.01 | -0.09 | 0.93 |
| Title 1, Targeted | -0.14 | -0.08 | -0.84 | 0.40 |
| Title 1, School Wide | -0.06 | -0.04 | -0.30 | 0.76 |

Evaluating the assumptions of regression, the bivariate correlations between the independent variables are significant but low to moderate suggesting no issues with multicollinearity. Additionally, plots of the residuals suggest a normal distribution (Figure 9). Finally, two cases had a studentized residual above the threshold of 3 (Pituch & Stevens, 2016; Williams, 2016), though they were retained as the leverage values were below 0.048 and the Cooks distances were below 0.11. All other cases had Cook's distances below 0.111, and leverage values below 0.065 (Pituch & Stevens, 2016).

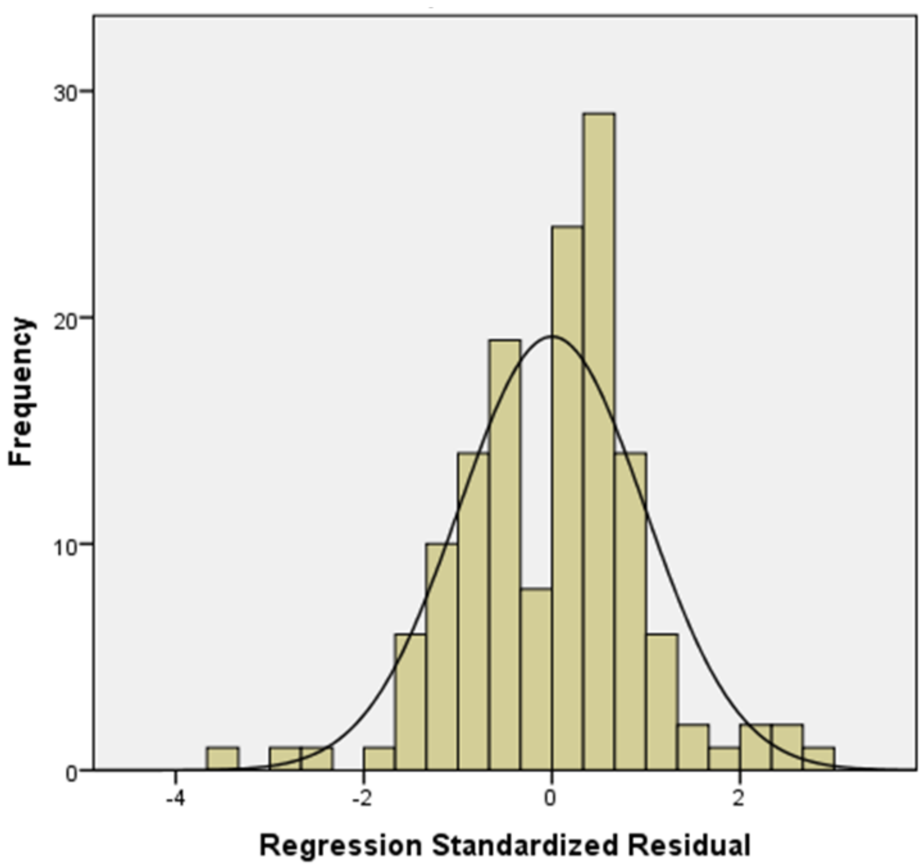


Figure 9 Histogram of the residuals from the linear regression of gender, race, and Title 1 status on student's growth in future aspirations in science

Summary, Phase Two

In the second iteration of the informal cognitive engagement and motivation in science (ICEMS) survey was analyzed using correlations and an exploratory factor analysis. The majority of the structure from the first phase of the study was retained suggesting good reliability. Five factors were again extracted that are theoretically aligned to the difference components of cognitive engagement (cognitive strategies and self-regulation), motivation (value and self-efficacy), and future aspirations in science. However, there are several differences in the factor structure given the changes made from the initial phase (e.g. addition of questions to measure self-regulation and self-efficacy). These changes resulted in less issues with cross-loading and had three items per factor (Beavers et al., 2013) and good reliability (Chronbach's alpha > 0.70).

The survey was administered pre- and post- which enabled an exploration of how the informal science experience impacted learners. Aggregated factor scores (cognitive strategies, self-regulation, value and self-efficacy) on the pre-survey were subtracted from the post-survey results. These differences were then analyzed to understand if participants of different genders, races, and socioeconomic statuses (school's Title 1 status) were impacted by the informal science experience differentially. As the factors measuring cognitive engagement (cognitive strategies and self-regulation) are correlated, they were explored using a multivariate analysis of variance (MANOVA). Results revealed significant interaction effects between race and Title 1 status on their growth in cognitive strategies. Though explaining only 7% of the variance, learners of color who attend schools that are not eligible for Title 1 funding gained significantly more $F(1, 136) = 8.01$, $p < 0.00$) in their reported levels of cognitive engagement than white learners attending schools who are not eligible for Title 1 funding.

Growth in value, self-efficacy, and future aspirations were evaluated independently using linear regression to understand differences between learners of diverse genders, races, and socioeconomic statuses. The linear combination of gender, race, and Title 1 status significantly predicted the growth in value ($R^2 = 0.09$), with gender being the only significant predictor. Results indicated that females grew more ($B = 0.24$, $p < 0.05$) than males in how much they value science. The linear combination of gender, race, and Title 1 status did not significantly predict growth in self-efficacy or future aspirations in science.

# CHAPTER FIVE: DISCUSSION

## Introduction

This chapter will review the major findings within the context of the theoretical framework, respond to the research questions, explore limitations and delimitations, and identify future areas of research. In keeping with the design of the study, this section will be divided into two parts. Phase One and Phase Two will be discussed individually, followed by a conclusion addressing the overall impact of the phases collectively. As both an orientation to the research questions and basic synopsis of the results, Table 28. provides an overarching response to the research questions that will be explored further in this chapter.

Table 28 Alignment of the research questions, data analysis techniques and an overview of the results

| Phase 1 | | |
|---|---|---|
| Research Question | Analysis Technique | Results |
| What survey questions operationalize cognitive engagement and motivation in science specific to informal contexts for middle school learners? | Correlation, Factor analysis, Partial-least squares structural equation modeling | 15 out of the 20 questions were used to operationalize cognitive engagement (cognitive strategies and self-regulation), motivation (value and self-efficacy), and future aspiration in science in an informal science context. A PLS-SEM model, showing acceptable model fit, testing the latent constructs measuring cognitive engagement and motivation significantly predicted future aspirations in science ($R^2$ = .31, $p < 0.05$). |

Table 28 Continued

| | | |
|---|---|---|
| What impact does informal science experiences have on middle school learner's future aspirations in science? | Paired samples t-test | As the survey was administered pre-post, the pre-scores on cognitive engagement (cognitive strategies and self-regulation), motivation (value and self-efficacy), and future aspiration in science were compared to the post scores. Post-scores on cognitive strategies, self-efficacy and future aspirations in science are significantly higher than in the pre- survey ($p < 0.01$). Learners did not report higher scores on self-regulation nor in the degree to which they value science ($p < 0.01$). |
| Phase 2 | | |
| Research Question | Analysis Technique | Results |
| What survey questions operationalize cognitive engagement and motivation in science specific to informal contexts for middle school learners? | Correlation, Factor analysis, | A revised 20 question survey was administered based Phase One results. Of these, 15 survey items were retained under 5 factors that theoretically align to cognitive engagement (cognitive strategies and self-regulation), motivation (value and self-efficacy), and future aspiration in science in an informal science context. |
| What impact does informal science experiences have on middle school learner's future aspirations in science? | Wilcoxon signed-rank test | As the survey was administered pre-post, the pre-scores on cognitive engagement (cognitive strategies and self-regulation), motivation (value and self-efficacy), and future aspiration in science were compared to the post scores. Post-scores on cognitive strategies, value, self-efficacy and future aspirations in science are significantly higher than in the pre- survey ($p < 0.01$). Post-scores on self-regulation, however like Phase One, did not increase in comparison to the pre-survey ($p < 0.01$). |
| As a result of an informal science experience, what is the relationship between middle school learner's cognitive engagement and their gender, race, and socioeconomic statuses? | Multivariate analysis of variance | The factors measuring the growth in cognitive engagement (cognitive strategies and self-regulation) during an informal science experience are correlated and they were explored together. Results show that only learners of color who attend schools not eligible for Title 1 funds had significantly higher growth in cognitive strategies as compared to white learners attending similar schools. |

Table 28 Continued

| | | |
|---|---|---|
| As a result of an informal science experience, what is the relationship between middle school learner's value of science and their gender, race, and socioeconomic statuses? | Linear Regression | In a linear combination, gender, race, and Title 1 status significantly predicted 9% of the variance in the growth in value during an informal science experience. The only significant predictor was gender ($p < 0.05$), with females growing more in their value of science than males. |
| As a result of an informal science experience, what is the relationship between middle school learner's self-efficacy in science and their gender, race, and socioeconomic statuses? | Linear Regression | In a linear combination, gender, race, and Title 1 status did not significantly predict growth in self-efficacy during an informal science experience. |
| As a result of an informal science experience, what is the relationship between middle school learner's future aspirations in science and their gender, race, and socioeconomic statuses? | Linear Regression | In a linear combination, gender, race, and Title 1 status did not significantly predict growth in future aspirations in science during an informal science experience. |

## Discussion, Phase One

Despite recognizing the role that informal science learning can play in developing interest and future career aspirations in STEM (Dabney et al., 2012; Nugent et al., 2015), and the important roles of cognitive engagement and motivation for any human endeavor, little is known about how to measure cognitive engagement and motivation in informal contexts. Therefore, to address the gap in research on cognitive engagement and motivation specific to informal science contexts, a measure of cognitive engagement and motivation for use in informal science contexts with middle school learners was developed. The ICEMS measure provides a conceptual basis for future research to explore these constructs using expanded methods and to better understand the connection between cognitive engagement, motivation, and future aspirations in science in informal contexts.

Data analysis resulted in three central theses. First, the ICEMS measure developed displayed preliminary reliability and validity. The PLS-SEM exploring the constructs in the ICEMS survey displayed acceptable model fit. Additionally, in comparing pre- and post-PLS-SEM models, there are no statistically significant changes in the path coefficients which supports overall model reliability as the magnitude and direction of the interactions between latent constructs did not change over the course of the informal science summer camp experience. This does not indicate that no changes occurred between the pre- and post-survey administration, rather that the changes did not impact the overall structure of the conceptual model evaluated via PLS-SEM.

In light of the multifaceted difficulties of assessing the impact of informal experiences, using cognitive engagement and motivation offers a unique approach that can provide an alternative to traditional content-knowledge focus measures (National Research Council, 2009). Results clearly demonstrate that informal contexts such as summer camps have the ability to foster learner’s future interest in science in addition to increasing their self-efficacy and cognitive strategy use. This finding is timely as calls mount to provide exposure of younger learners to the STEM fields (Council, 2011; National Research Council, 2013).

Tools like the ICEMS can help quantify the impact of these experiences, enabling practitioners to optimize their programming or experiences to foster cognitive engagement and motivation. First, the ICEMS is a survey measure, which can be easily implemented online, thus making it easy to implement and collect data for a program. Second, since the scales are consistent in the ICEMS, data analysis is simple, and the practitioner doesn't need to use advanced statistical software in order to understand the areas in which their program either increased, decreased, or did not change cognitive engagement, motivation, or future aspirations in science (Alrech & Settle, 2004).

Second, considering the importance of developing learner's desire to pursue science in the future, with an end goal of pursuing or understanding science in the future, explaining close to a third of the variance in future aspirations in science draws attention to the major functions that cognitive engagement and motivation plays in this process (Figure 2). Notably, while the results of the study show some evidence for a direct relationship between cognitive engagement and future aspirations in science as cognitive strategies are a significant predictor (Table 10, total effect = 0.17, $p < 0.05$), the motivational constructs of value (Table 10, total effect = 0.53, $p < 0.05$) and self-efficacy (Table 10, total effect = 0.19, $p < 0.05$) are better predictors of future aspirations in science. These findings reinforce the potential benefits of informal science experiences as rich areas for additional research on motivation (Lebeau et al., 2001). The results also beg the question, What accounts for the remaining variance within future aspirations in science? Whether science capital or other sociocultural factors (Archer et al., 2012), can account for this remaining variance was the focus of the Phase Two study.

Third, as expected, learner's ICEMS survey scores showed statistically significant gains for future aspirations, self-efficacy, and cognitive strategies over the course of the informal science experience (Table 12). Contrary to expectations, learners' scores related to the perceived value of science and self-regulation showed non-statistically significant changes. In other words, informal science summer camps have differential impacts on learners' overall cognitive engagement and motivation, promoting some but not all aspects of these meta-constructs. This finding may be explained by the immersive nature of the experience as it was a week-long and residential program to learners. Affective components such as lower energy levels at the ends of an intensive experience and being apart from family and friends may have mediated learner's perception of the importance and usefulness of science. The lack of statistically significant increases in the perceived value of science could point to issues with the specific aspects of value that can quickly be measured in informal contexts. For some learners, the value of the experience may be related to factors concerning the context of the camps such as its residential, co-ed nature, or its base in a university setting rather than the experiences connection to STEM. Additionally, the decline in self-regulation scores from before to after the camps could reflect how these skills were operationalized in the survey or the degree to which to informal experience was perceived to have affected those skills. Survey items targeting goal-setting or self-monitoring may be worthwhile inclusions in future iterations of the ICEMS survey (Miller et. al, 1996; Greene et al., 2004) and are tested in Phase Two.

However, it may also be the case that informal science experiences such as summer camps may not promote self-regulation skills. Therefore, studies that investigate the factors that help facilitate self-regulation, particularly with regard to the amount of scaffolding the learning environment (Yoon et al., 2013), may illuminate the utility of informal contexts to increase this skill set.

## Limitations and Implications for Future Research, Phase One

As with any self-report survey, the values reported by the participants may not be indicative of actual level of engagement or motivation. Greene (2015) argued that while self-reported measures have faced criticism, "much of motivation is about perception of the context and the self in the context" (p. 27). Further, Aschbacher et al. (2014), stressed the role that self-perceptions play in understanding motivation, thereby reinforcing the importance of self-reported measures (p.736). Though Greene (2015) concluded that research should go beyond self-reported measures, given the lack of literature on engagement and motivation in informal settings, the creation of the ICEMS survey offers a useful starting point by which to use expanded methodologies and triangulate findings.

The ICEMS survey may also benefit from additional refinement. Specifically, four of the initial survey questions chosen to measure cognitive strategies, self-efficacy, and self-regulation did not factor as expected. This left only two survey items measuring self-efficacy and self-regulation constructs, a limitation which may be seen in lower Chronbach's alpha scores (see Table 9).

Finally, this study makes no claims about the impact duration. It is possible that gains seen over the course of these informal science experiences could be short lived or they could be lasting changes. Additional studies looking at the long-term impacts of informal experiences would, therefore, be helpful and future studies may consider using indicators of cognitive engagement and motivation. Lastly, since this tool was created specifically for middle school learners, evaluating the instrument in varied contexts with varied ages and diverse backgrounds would provide an understanding for the ability of the ICEMS to work with learners in different grades and diverse audiences.

## Discussion, Phase Two

As setup by Phase One, fostering learner interest in STEM and gaining STEM-specific skills are important, both to the long-term viability of growth in the United States and to the success of an individual in an increasingly complex global lived reality (National Research Council, 2012). Informal science experiences can be areas to explore learner's engagement, motivation and future aspirations in science (Chittum, 2017; Phase One results), yet tools to measure these constructs in informal settings are limited. Phase Two aimed to refine issues revealed in Phase one with the Informal Measure of Cognitive Engagement and Motivation in Science (ICEMS) survey.

The largest change from Phase One to Phase Two was the re-formulation of the ICEMS survey. From Phase One, of the 16 items retained in the factor analysis, only 2 survey items were used to measure learner's self-efficacy and self-regulation in informal science contexts. To address these, four additional survey items were added to the second iteration of the ICEMS survey. Other changes between Phase One and Phase Two of the study includes the collection of racial demographic information. The addition of this intersection to the existing demographic information of gender and socioeconomic (Title 1) status enabled a better exploration of informal science contexts as "third spaces," or educational settings that do not have the same persistent inequalities as formal settings (Archer et al., 2012). According to Bourdieusian theory, educational experiences can provide participants with social, or in this case, science, capital that can be used to provide a future advantage. Informal learning experiences have the potential to act as "third spaces" and provide participants with science capital as they are typically voluntary, self-directed, and open-ended, which can stand in contrast to formal educational settings (Wellington, 1990).

Again, data analysis resulted in three central theses. First, the ICEMS measure created displayed good reliability and validity. The ICEMS survey continues to offer a unique approach that can provide an alternative to traditional content-knowledge focus measures (National Research Council, 2009). Four questions retained in Phase One were dropped in Phase Two, replaced by three new questions added to better explain cognitive strategies, self-efficacy, and self-regulation. The changes made during Phase Two increased the reliability of each of the latent constructs measuring cognitive engagement and motivation from Phase One to Phase Two, Table 29. In addition, the retention of 75% of the survey items (12 out of 16 items), with 69% of these factoring into the same theoretical construct, suggests good reliability.

Table 29 Chronbach's alpha for the latent constructs in Phase One and Phase Two measured in the pre-surveys

| Phase One | | Phase Two | |
|---|---|---|---|
| **Construct** | **C. Alpha** | **Construct** | **C. Alpha** |
| **Cognitive Strategies** | **0.56** | **Cognitive Strategies** | **0.76** |
| **Self-Regulation** | **0.68** | **Self- Regulation** | **0.82** |
| **Value** | **0.80** | **Value** | **0.77** |
| **Self-Efficacy** | **0.53** | **Self- Efficacy** | **0.78** |
| **Future Aspirations** | **0.79** | **Future Aspirations** | **0.77** |

**Note. C. Alpha, Chronbach's alpha**

Each of the items included in the survey have a theoretical basis in the literature and many of the items are taken directly or only with slight modification from existing tools (Miller et al., 1996: Pintrich & De Groot, 1990), which does add credence to the tool's construct validity. In summary, the ICEMS survey has improved and shows good reliability and validity for use with middle school learners in informal science contexts.

Second, much like Phase One, learner's ICEMS survey scores showed statistically significant gains for future aspirations, value, self-efficacy, and cognitive strategies over the course of the summer camp experience (Table 18). However, learners' scores related to self-regulation showed non-statistically significant changes, a finding also evidenced in Phase One. The non-statistically significant gain in self-regulation scores between the pre-and post-survey, could reflect how these skills were operationalized in the survey or the degree to which the informal experience was perceived to have affected those skills. However, given the acceptable Chronbach's alpha scores and the theoretical basis of the questions included in the measurement of this construct, it may be that this informal science experience did not promote the development of self-regulation skills. The week-long summer camp was structured in that there were schedules set in place that the participants were asked to follow. As a result, learners may not have had the opportunity to try difficult experiences over again or be given the space by which to take their time to persist in the face of a difficult challenge. Additional studies that explore this potential tradeoff, particularly with respect to Yoon et al.'s (2013) work on the concept of "over-formalization," may be critical. Their research suggests a possible concern about how an "over-formalization" of the learning process may restrict the experiences of the learners in informal contexts, noting that, "as scaffolds were added to the learning environment, informal behaviors [ such as experimentation and learner-generated questions] tended to decrease" (Yoon et al., 2013, p. 865).

Lastly, exploring the impact of an informal science experience has shed light on these experiences to be learning contexts that do not continue to reinforce inequalities persistent in formal educational systems (Baker et al., 2014; Cannady, Greenwald, & Harris, 2014). Bourdieu's (1986) theories around culture suggest that structures of privilege, or in this study inequality, are reinforced through interaction of habitus, capital and field. Following this theory, a person's way of being and their access to resources or experiences of value interact with a given context to either provide the person an advantage or disadvantage (Lareau, 2011). These theories have been expanded to include science capital (Archer et al., 2015; Archer et al., 2012; Lareau, 2011), to explain the inequalities that persist in STEM education and workforce development. Archer et al. (2015) suggested that where underrepresented populations are able to draw on science-related capital, it may facilitate overcoming issues with habitus and field in order to maintain an interest in pursuing STEM.

Using learner's gender, race, and ethnicity, Phase Two investigated whether informal science experiences differentially impacted learners' cognitive engagement (cognitive strategies and self-regulation), motivation (value and self-efficacy), and future aspirations in science by using learner's growth in these factors. No differences between learners' intersections were found with regard to how an informal science experience impacted learner's self-regulation, self-efficacy, or future aspirations in science. Interestingly, there were differences in cognitive strategies and value of science. Learners of color who attend schools not eligible for Title 1 funds grew more in cognitive strategies than their white counterparts. In addition, females grew in their value of science more than their male counterparts during the informal science experience. An important note of both of these claims is that the analyses explained 6% and 8% of the variance, respectively. Findings that indicate in both cases only about 8% of the differences in growth in either cognitive strategies or value can be explained by a learner's gender, race, or socioeconomic status in this study. Regardless, these differences might be seen as evidence that informal science learning may provide avenues for underserved or underrepresented populations to develop science capital. The lack of differences found in the growth of learners' value, self-efficacy, and future aspirations in science is certainly evidence that informal contexts may be equitable spaces to experience science, which given the persistent inequalities in formal contexts, is a finding worth replicating with a larger sample size and with difference informal science experiences.

Limitations and Implications for Future Research, Phase Two

Akin to Phase One, any self-report survey has shortcomings as the values reported by the participants may not be indicative of actual level of engagement or motivation. However, every approach to measuring an experience has shortcomings, whether quantitative or qualitative, and given the lack of literature on engagement and motivation in informal settings, refining the ICEMS survey will allow future studies to have a more reliable and valid tool by which to either complete a baseline analysis or triangulate findings.

The motivational construct, self-regulation, may benefit from additional iteration. While it was based in the literature and displayed good reliability, the fact that, in both Phases, learners did not report gains, may indicate issues with the operationalization in this context. It is possible that, rather than modifying the ICEMS survey instrument, that a different method such as interviews or observations may illuminate a new theoretical direction for the concept in informal science contexts.

Finally, as with Phase One, this study makes no claims about the longitudinal impact of an informal science experience or learners' cognitive engagement and motivation. As suggested by Falk's contextual model of learning, learners' understanding changes over time and exploring either the factors that increase the impact duration of informal learning experiences or the aspects of the experience that facilitated a lasting impression are avenues of future research. Lastly, since this tool was created specifically for middle school learners, it would need to be modified to be used in ages or abilities beyond this range.

Finally, because a focus of Phase Two was how informal science experiences impact learners of varying gender, race, and socioeconomic status, relying on surveys likely underestimates the actual diversity present in the learners. For example, the camp application question asking for learners to provide their race was based on the U.S. Census categories (United States Census Bureau, 2000) and may have denied people the ability to show their unique cultural heritage (Montana Office of Public Instruction, 2012), particularly in light of the large presence of American Indian/ Native American learners involved in this study. Further descriptive and correlational studies could allow a more nuanced approach to obtaining demographic intersections in order to better understand how informal science experiences might impact learners.

## Conclusion

An overarching goal of this study was to explore cognitive engagement and motivation in informal science contexts. There is great promise in informal contexts to help support the growth and development of active and knowledgeable citizens (National Research Council, 2009). Learning and experiencing scientific phenomenon in a voluntary, open-ended manner enables the learner to direct the process based on their own goals and objectives, resulting in a fluid and dynamic approach to education (Wellington, 2013). As such, exploring how and what people learn in these contexts may provide potentially powerful tools. Methods and findings emerging from such investigations could help increase the ability of formal education to be responsive and effective, overcoming persistent inequalities and barriers to equitable STEM education (Baker et al., 2014). Continued exploration with expanded methodologies and methods could help to further elucidate these relationships and the impact on participants. Qualitative studies using observations and interviews may help to better understand the learner's own journey through the informal science experience. An ethnographic or narrative exploration of may illuminate the social patterns present in the community and how these social or structural components influence individual learner development in informal contexts. However, even additional quantitative studies using the ICEMS tool in different informal science contexts, such as museums, zoos, or nature centers, may shed light on the relationships between cognitive engagement, motivation, and future aspirations in science, particularly as they are developed by diverse students.

The importance of cognitive engagement (Greene, 2015; Greene, Miller, Crowson, Duke, & Akey, 2004) and motivation (Hulleman & Harackiewicz, 2009; Wigfield & Eccles, 2000) in education cannot be undervalued as both of these meta-constructs have been tied to an increase in educational outcomes for years (Fredricks, 2011; Fredricks et al., 2004; Fredricks & McColskey, 2012; Martin et al., 2016). A number of methods and approaches have been used to explore these constructs in formal settings, however, the number of tools to explore how these constructs develop in informal contexts is limited (Chung et al., 2016). The development of the Informal Cognitive Engagement and Motivation in Science (ICEMS) scale offers informal educators a useful pre-post survey tool by which to evaluate the impact of their programs and assess or hone their educational outcomes. Through Phase One and Phase Two of this study, the ICEMS tool has been updated and the reliability and validity of the tool has been improved, enabling practitioners to have a tool that produces results that are a good approximation of cognitive engagement and motivation in science. Particularly with surveys, practitioners or those without formal evaluation or research training can implement and investigate the impact of their interventions without much effort. Thus, the ICEMS gives general practitioners access to a low-impact and low-cost way to improve their educational programming in order to foster cognitive engagement and motivation.

In developing the ICEMS tool, Phase One and Phase Two of this study have been able to shed light on informal contexts as rich laboratories to study learners' future aspirations in science, cognitive engagement and, motivation, both in theory and practice. First, Phase One found that upwards of 30% of learners' future aspirations in science can be explained by the combination of cognitive engagement (cognitive strategies and self-regulation) and motivational (value and self-efficacy) variables ($p < 0.05$). Suggested by Archer et al. (2015), Martin et al. (2016), and Chittum (2017), informal contexts can certainly influence learners' interest in and desire to pursue STEM in the future, being it in their future coursework or seeing STEM careers as viable options for them. Second, where this study diverges from the literature base is in the predictive ability of cognitive engagement and motivational variables on outcomes. Commonly,

> Most authors – motivation and engagement researchers alike – postulated that motivation is an antecedent or precursor of engagement, echoing a view offered several years ago by Russell, Ainley, and Frydenberg (2005) that motivation is intent and engagement is action. This view allows for the

> merging and coexistence of the rich, distinguished history of motivational research with the more nascent and intervention focused field of engagement, thereby linking motivation to engagement and, in turn, to important outcomes of interest to scholars, parents, and educational personnel (Christenson, Reschly, & Wylie, 2012, p. 814)

Yet, Phase One's PLS-SEM model demonstrated that, while both cognitive engagement and motivational variables influence learners' future aspirations in science, it is the motivational variable of value that is the strongest indicator (Table 10, total effect = 0.53). This finding challenges the notion that engagement is a strong mediator of motivation. Continued exploration of the nature of engagement and motivational variables may help to clarify a confusing and sometimes contradictory literature base, particularly given the promise of engagement as the "holy grail of learning" (Sinatra, 2016, p 1.).

An important limitation to discuss within the context of this study is the significance of focusing on cognitive engagement and motivation as they relate to learners' future aspirations in science rather than other indicators or educational outcomes such as behaviors or learning (e.g. content knowledge, skills, or processes). In measuring cognitive engagement, there is a lack of focus on the other dimensions of engagement (affective and behavioral) and using the outcome of future aspirations in science certainly does not encapsulate the total outcomes of informal science experiences. Taken together, these limitations beg the questions, what is important to measure and what outcomes should come from informal science experiences? Answers to these questions are far more complicated and likely cannot be summarized in a single response besides, "it depends," or as Reynolds & Chiu (Reynolds & Chiu, 2013) might respond, "it depends on the context." Some scholars, like Wellington (1990) might feel these questions are too constrained to handle the natural variation, and associated power, of learning in informal contexts. Others, like the National Research Council (2009), might argue that not assessing or evaluating the impact of these experiences hinders the ability of programs to improve and respond to the growing needs of our society at large. Each viewpoint does suggest a different desire for learning in informal contexts. Therefore, a significant impact of this study might be to encourage conversation amongst practitioners and researchers to decide why the programs or experiences being offered are important. Then established tools, like the ICEMS, could be implemented to best support the continued growth and development of effective practice.

Finally, while certainly limited in scope, this study does add to the discussions currently led by Archer et al. (2015), surrounding informal contexts as spaces where underrepresented or underserved populations can cultivate science capital in equitable ways. Exploring the differences within and between learners of difference gender, race, and socioeconomic status in this study as they relate to cognitive engagement, motivation, and future aspirations in science in middle school, and finding that there are either no differences or that these populations gain more in informal science contexts is intriguing. Particularly in light of the potential importance of cognitive engagement and motivational skills to success in formal educational contexts, if underserved or underrepresented populations can have access to informal science, these experiences may be a key to supporting their academic development. Of critical note, it is essential to recognize that, even if informal contexts truly are "third spaces," and help support the growth and development of STEM literacy or interest equitably, this finding does not preclude formal contexts from needing to make necessary changes. Informal learning can be discussed as an antidote to the systemic issues of STEM in the formal educational system (Riegle-Crumb, Moore, & Ramos-Wada, 2011; Sadler, Sonnert, Hazari, & Tai, 2012), yet to do so has the potential to shift focus away from factors relating to habitus, capital, and field that reinforce the inequitable system of privilege and dominance in formal education (Archer et al., 2012; Bourdieu, 1986; Cannady et al., 2014). A final recommendation from this study is to explore the systematic factors that enable informal spaces to not discriminate between learners based on demographic indicators and use these factors to inform practice in formal spaces. In this manner, formal systems might function more equitably regardless of access to external informal learning opportunities.

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# APPENDICES

# APPENDIX A

## INFORMAL MEASURE OF COGNTIVE ENGAGEMENT AND MOTIVATION,

## PHASE ONE SURVEY

| | |
|---|---|
| Value | |
| Pre ICEMS-Survey Items | Abbreviation |
| I want to be challenged to learn new things in science this week. | Challenge |
| What I am learning about this week can be used to help improve my community. | Community |
| I am excited about the science activities this week. | ExcitedSci |
| Learning science this week is important for achieving my future goals. | Important |
| What we are learning about this week will be interesting. | Interesting |
| Self-Efficacy | |
| Pre ICEMS-Survey Items | Abbreviation |
| I feel that I can complete all of the science activities this week. | Complete |
| I expect to do well in the science activities this week. | DoWell |
| Cognitive Strategies | |
| Pre ICEMS-Survey Items | Abbreviation |
| This week, it's okay to make mistakes when learning science. | Mistakes |
| When I run into a difficult science activity this week, I try until I figure it out. | DifficultTry |
| I think about how new science activities relate to things I already know. | PriorKnow |
| I try to understand new science material even if it doesn't make sense at first. | TryNoSense |
| Self-Regulation | |
| Pre ICEMS-Survey Items | Abbreviation |
| When a science activity is hard, I either give up or learn only the easy parts. * | DifficultEasyParts* |
| When I run into a difficult science activity, I usually give up and move on. * | DifficultGiveUp* |
| Future Aspirations | |
| Pre ICEMS-Survey Items | Abbreviation |
| I am interested in going to college for science. | College |
| c | HighSchool |
| I am interested in having a job that uses science. | Job |
| Value | |
| Post ICEMS Survey Items | Abbreviation |
| This week, I wanted to be challenged to learn new things in science. | Challenge |
| What I learned this week can be used to help improve my community. | Community |
| I was excited about the science activities this week. | ExcitedSci |

| | |
|---|---|
| Learning science this week was important for achieving my future goals. | Important |
| What I learned this week was interesting. | Interesting |
| Self-Efficacy | |
| Post ICEMS Survey Items | Abbreviation |
| I feel that I completed all of the science activities this week. | Complete |
| I did well in the science activities this week. | DoWell |
| Cognitive Strategies | |
| Post ICEMS Survey Items | Abbreviation |
| This week, it was okay to make mistakes when learning science. | Mistakes |
| This week, when I ran into a difficult science activity, I tried until I figured it out. | DifficultTry |
| This week, I thought about how new science activities relate to things I already know. | PriorKnow |
| I tried to understand new science material this week, even if it didn't make sense at first. | TryNoSense |
| Self-Regulation | |
| Post ICEMS Survey Items | Abbreviation |
| This week, when a science activity was hard, I either gave up or only learned the easy parts. * | DifficultEasyParts* |
| When I ran into a difficult science activity, I usually gave up and moved on. * | DifficultGiveUp* |
| Future Aspirations | |
| Post ICEMS Survey Items | Abbreviation |
| The camp made me more interested in going to college for science | College |
| The camp made me want to take more high school science classes. | HighSchool |
| The camp made me more interested in having a job that uses science. | Job |

*Items were reverse coded

# APPENDIX B

## PHASE TWO INFORMAL COGNITIVE ENGAGEMENT AND MOTIVATION IN SCIENCE SURVEY ITEMS

| Value | |
|---|---|
| **Pre ICEMS-Survey Items** | **Abbreviation** |
| What I am learning about this week can be used to help improve my community. | Community |
| Learning science this week is important for achieving my future goals. | Important |
| What we are learning about this week will be interesting. | Interesting |
| **Self-Efficacy** | |
| **Pre ICEMS-Survey Items** | **Abbreviation** |
| I feel that I can complete all of the science activities this week. | Complete |
| I know I can learn the science ideas and skills taught this week. | CanLearn |
| I expect to do well in the science activities this week. | DoWell |
| **Cognitive Strategies** | |
| **Pre ICEMS-Survey Items** | **Abbreviation** |
| I feel that I will use good strategies to learn science ideas and skills this week. | GoodStrategies |
| I am willing to work hard to do well in science this week even when I don't like it. | WorkHard |
| I try to understand new science material even if it doesn't make sense at first. | TryNoSense |
| **Self-Regulation** | |
| **Pre ICEMS-Survey Items** | **Abbreviation** |
| When a science activity is hard, I either give up or learn only the easy parts. * | DifficultEasyPart* |
| When I run into a difficult science activity, I usually give up and move on. * | DifficultGiveUp* |
| When I run into a difficult science activity this week, I try until I figure it out. | DifficultTry |
| **Future Aspirations** | |
| **Pre ICEMS-Survey Items** | **Abbreviation** |
| I am interested in going to college for science. | College |
| I want to take high school science classes. | HighSchool |
| I am interested in having a job that uses science. | Job |

| Value | |
|---|---|
| **Post ICEMS Survey Items** | **Abbreviation** |
| What I learned this week can be used to help improve my community. | Community |
| Learning science this week was important for achieving my future goals. | Important |

| | |
|---|---|
| What I learned this week was interesting. | Interesting |
| Self-Efficacy | |
| Post ICEMS Survey Items | Abbreviation |
| I feel that I completed all of the science activities this week. | Complete |
| I know I learned the science ideas and skills taught this week. | CanLearn |
| I did well in the science activities this week. | DoWell |
| Cognitive Strategies | |
| Post ICEMS Survey Items | Abbreviation |
| I felt that I used good strategies to learn science ideas and skills this week. | GoodStrategies |
| I was willing to work hard to do well in science this week even when I didn't like it. | WorkHard |
| I tried to understand new science material this week, even if it didn't make sense at first. | TryNoSense |
| Self-Regulation | |
| Post ICEMS Survey Items | Abbreviation |
| This week, when a science activity was hard, I either gave up or only learned the easy parts. * | DifficultEasyParts* |
| When I ran into a difficult science activity, I usually gave up and moved on. * | DifficultGiveUp* |
| This week, when I ran into a difficult science activity, I tried until I figured it out. | DifficultTry |
| Future Aspirations | |
| Post ICEMS Survey Items | Abbreviation |
| The camp made me more interested in going to college for science | College |
| The camp made me want to take more high school science classes. | HighSchool |
| The camp made me more interested in having a job that uses science. | Job |

*Items were reverse coded