

How Teacher Self-efficacy and Mindset Influence Student Engagement and Math
Performance

A Dissertation

SUBMITTED TO THE FACULTY OF THE
UNIVERSITY OF MINNESOTA

BY

Andrew Jordan Thayer

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

Clayton R. Cook, Ph.D. and Amanda L. Sullivan, Ph.D., Advisers

© Copyright 2020 by Andrew Jordan Thayer

All Rights Reserved

Acknowledgments

This dissertation is the culmination of an indispensable period of personal exploration, challenge, and growth. In that, it is more than words on a page, thoughts and convictions tested. I set out years ago to prove to myself that I could complete a doctorate degree. Thus, it is a monument to that goal attainment and a stark example of the criticality of perseverance, humility, and, most important, relationships in my work and life. I did not achieve this alone. Many people deserve recognition and gratitude for their encouragement, companionship, and mentorship. I only hope my words adequately convey how much I appreciate these important people in my life.

I gratefully acknowledge the contribution and guidance of my advisors, Drs. Clay Cook and Amanda Sullivan, whose compassion, succor, and personal dedication to my development were invaluable. My progress in the program has felt winding and unorthodox. At times, I felt compelled to quit. I recall several conversations with them that strengthened my resolve and eliminated both internal and external barriers. I truly credit much of my progress—in this milestone, the program, and personally—to these stellar mentors.

I also want to acknowledge the insight and time dedicated to this project by my dissertation committee chair Dr. Darin Erickson. Dr. Erickson and I first met preparing for the 2017 Sloboda Cup. He offered great mentorship and guidance during that enjoyable and valuable learning experience. More so, he widened my perspective about what psychology can do for the public good. Our musings over the philosophy of science and deep probes into the concepts and methods incorporated in my dissertation deepened my understanding and competency in immeasurable ways.

I do not consider myself a methodologist, but I have developed a skillset in bridging content and methods. Dr. Nidhi Kohli has been one of my biggest supporters in this venture. Our first meeting remains one of the most defining moments in graduate school, as it revealed just how much I had yet to learn and the importance of doing things *right*, even when difficult and time-consuming. I consider myself lucky to have her as a mentor and model. Wherever my career takes me, I welcome more opportunities to work and learn together.

To Dr. Robin Coddling, you have been a critical support throughout this dissertation and my progress in graduate school. Your precision and technique with your work, motivations and values as a researcher, dedication to our development as scientists and practitioners, and general openness have always been appreciated and valued. In truth, I hope to demonstrate similar qualities in my own career.

I am incredibly grateful for the influence of Drs. Faith Miller, Annie Hansen-Burke, and Theodore Christ as faculty mentors in the school psychology program. Dr. Miller's insight on the needs of children with emotional difficulties was critical during

my second year and keenly responsible for my interest in working with these children. Dr. Christ was and remains a mentor and model for critical thought and deep intrinsic engagement with purposeful work. Your guidance in my early years instilled in me a respect for scientific inquiry and investigation that will continue into my career. Dr. Hansen-Burke's camaraderie, positive support, and engaging instruction was core to my education experience. I still have an incredibly encouraging email you sent in my first year that I reflect on periodically.

The journey toward completing this dissertation began with a group of friends and colleagues to whom I am indebted. We were and hopefully will always be quite the crew. Your positivity, wonder, support, and joy for life permeated throughout, bringing a character and dynamism to graduate school that I would not trade. I am excited to continue in this profession with you and witness the good you all do.

This acknowledgement section would be incomplete without recognizing the contribution and support of (soon to be Dr) Alyssa Schardt. I think the similarity in our circumstances starting graduate school brought us together in shared values, struggles, and achievements. After five years, I am glad to say that you are my best friend and an invaluable source of fun, emotional support, and needed straightforward honesty.

Finally, to my family—my mother Valerie, and brothers Jon and Josh. We have been through so much and this dissertation coincides with pivotal moves and changes in our lives. Thank you for your support throughout it all. I look forward to seeing where our lives continue to go and how we squeeze all the good out of them.

“It does not matter how slowly you go as long as you do not stop.”

-Confucius

Abstract

Research continues to support the association between school engagement and math achievement, and active engagement in early elementary mathematics education appears to cascade into long-term math achievement. Teacher beliefs about themselves and their students and their behavior has the potential to influence student engagement and achievement. This study investigated how teacher self-efficacy, teacher implicit theories of intelligence, and the effectiveness of their math instruction practices influence multiple domains of student engagement and achievement. Using structural equation models, the relative importance of teacher beliefs and behaviors were explored. Specifically, the hypothesis that a teacher's instructional behavior mediated the influence of their beliefs on students' mathematics outcomes was tested. In order to determine how different subgroups of teachers influence student outcomes, mixture modeling was used to classify teachers according to their beliefs and behaviors. Results were unexpected and did not support initial hypotheses. Teachers' self-efficacy and instructional effectiveness were not related to dimensions of student math engagement and performance. Teachers' implicit theories about their students' intelligence evidenced a positive relationship with behavioral engagement. Four teacher subgroups were identified that differed primarily in their implicit theories. There were mostly no differences in student outcomes between teacher subgroups. Implications for research, theory, professional development, and measurement are included.

Table of Contents

Acknowledgments.....	i
Abstract.....	iii
List of Tables	vi
List of Figures.....	vii
Chapter 1: Introduction.....	1
Importance of Student Engagement	1
Teachers' Influence on Engagement.....	4
Teachers' Implicit Theories of Intelligence	8
Teacher implicit theories in math.....	11
Rationale and Purpose: What Matters More, Instruction or Teacher Beliefs?.....	12
Chapter 2: Literature Review.....	19
Multi-level Influences on Student Performance.....	20
Teachers Are Proximal Social Actors	21
Teachers' Own Social-Cognitive Characteristics	23
Teacher self-efficacy	24
Teacher implicit theories of student intelligence.....	26
Interplay between Classroom Practices and Social-cognitive Characteristics.....	29
Pros and Cons of Variable- and Person-centered Analytic Methods.....	35
Summary of Literature Review	37
Chapter 3: Method	39
Sampling.....	40
Recruitment.....	40
Measures.....	41
Teacher social-cognitive factors.....	43
Instructional effectiveness.....	45
Teacher background	46
Student engagement.....	46
Math achievement.....	49
Analysis Plan.....	50
Analytic Sample.....	51

Research question 1	51
Research question 2	56
Chapter 4: Results	61
Descriptive Statistics	61
Teacher Self-efficacy and Instructional Model (Base Model)	71
Teacher Self-efficacy, Instruction, and Implicit Theory Model (Mindset Model)	73
Partial Mediation Model.....	75
Latent Class Analysis	76
Teacher Latent Class Analysis Regression	81
Predicting teacher classes.	82
Classes predicting student outcomes.	87
Chapter 5: Discussion	91
Implications for Research and Practice	99
Limitations	102
Conclusion	106
References.....	108

List of Tables

Table 1. Description and abbreviation used for all items.....	39
Table 2. Demographic statistics as means and proportions.....	57
Table 3. Zero-order correlations, means, and standard deviations of all indicator and outcome variables.....	61
Table 4. Fit statistics and convergence error problems for 2-8 Teacher Class (TC) models.....	71
Table 5. Average latent class probabilities for the most likely class membership (on rows) based on what class teachers were ultimately assigned (on columns).....	72
Table 6. Model fit statistics for logistic regression models predicting TC membership...	76
Table 7. Predicting class membership using a teacher's experience (in years) and related training variables (model 3).....	77
Table 8. Multivariate simple regression outcomes using class to predict behavioral engagement.....	81
Table 9. Multivariate simple regression outcomes using class to predict math performance.....	82

List of Figures

Figure 1. Base Model.....	13
Figure 2. Mindset Model.....	14
Figure 3. Mediation Model.....	15
Figure 4. Social-cognitive logic model.....	27
Figure 5. Teacher latent classes predict student engagement and achievement.....	54
Figure 6. Base Model results.....	66
Figure 7. Mindset Model results.....	68
Figure 8. Partial Mediation Model results.....	70
Figures 9-12. Profile analysis of indicator means for LCA models with 2-5 classes..	73-75

Chapter 1: Introduction

Student engagement—understood broadly as how students think, feel, and behave in school (Finn & Zimmer, 2012)—is positively associated with a range of short- and long-term outcomes (Fredericks, Bulumenfeld, & Paris, 2004; Martin, 2006). Research consistently supports the association between engagement and mathematics achievement (Everingham, Gyuris, & Connolly, 2017; Fung, Tan, & Chen, 2018; Lein et al., 2016; Leon, Medina-Garrido, & Núñez, 2017), which is, in turn, considered central to educational attainment and overall quality of life (Bodovski & Farkas, 2007; National Mathematics Advisory Panel, 2008). Numerous factors can affect students' engagement, but among the most influential and *malleable* are characteristics of teachers, particularly their social-cognitive beliefs about themselves (e.g., Midgley, Feldlaufer, & Eccles, 1989), their students (Jussim & Harber, 2005), and their instructional practices (e.g., Skinner & Belmont, 1993). In a context of mounting emphasis on evidence-based practice, understanding of relations of these factors to students' outcomes may support our efforts to bolster mathematics achievement. This dissertation employs structural equation modeling and mixture modeling to ascertain (a) how teachers' social-cognitive beliefs (self-efficacy and implicit theory of math intelligence; Hong, Chiu, & Dweck, 1995) and mathematics instructional practices are similarly or differentially related to students' engagement and mathematics achievement, (b) if instructional practices mediate the relations between teachers' beliefs and students' engagement, and (c) if latent profiles based on these teacher-level factors predict students' engagement and math achievement.

Importance of Student Engagement

Researchers have defined student engagement in numerous ways, with no widely agreed upon definition of the construct. Several theoretical models have been proposed, with varying amounts of empirical support. One of the more commonly cited models is the multi-factor model proposed by Reschly, Appleton, and Christenson (2007), which posits four inter-connected engagement domains (academic, affective, behavioral, cognitive) that coalesce into a single engagement construct. According to this model, academic engagement reflects the physical act of completing academic assignments and degree matriculation (e.g., time on-task, homework completion, classes passed). Affective engagement reflects how a student feels about their school and classroom. Specifically, this domain captures students' sense of classroom belonging, their connection and collaboration with other students, the extent to which they perceive their teachers as emotionally supportive, and teacher-student relationship quality (Finn & Rock, 1997; Reschly & Christenson, 2012). Behavioral engagement reflects on-task, cooperative and non-disruptive behavior in the classroom during lessons (Appleton, Christenson, & Furlong, 2008), as well as general attendance and participation in school-wide activities. Cognitive engagement refers to a student's motivation, enjoyment, and interest in the learning process and didactic content (Reschly, Phol, Appleton, & Christenson, 2017). It differentiates students who find value, meaning and intellectual stimulation in their school work from those who do not. Students can exhibit varying degrees of engagement along these dimensions. Some models (e.g., Martin, 2007) posit positive and negative valences to dimensions of engagement. Broadly, then, the construct of student engagement can be understood as how students positively and negatively

think, feel, and behave in school, with positive engagement critical for healthy academic development and learning (Finn & Zimmer, 2012).

Student engagement warrants researcher and educator attention primarily because of its critical role as a protective factor against school failure and eventual dropout (Finn & Zimmer, 2012), as well as being an explicit component of some well-being models (see for example, Seligman, 2011). School failure and dropout are often the result of cumulative risk factors including economic disadvantage, unstable family structure, English as a second language, ethnic/cultural minority, early behavior problems, and early academic problems (Finn & Zimmer, 2012). Many of these factors are intractable or require extensive effort to alter. Positive student engagement, however, can serve as a protective factor for students with high cumulative risk. One way that student engagement buffers them from the detrimental effects of risk factors is through enhanced mathematics achievement (Attewell & Domina, 2008; Gutman, Sameroff, & Eccles, 2002). From an ecological perspective (Bronfenbrenner, 1977), there are several avenues through which student engagement can be bolstered. Much of the previous research on correlates of engagement have focused on individual characteristics, and micro- and macrosystemic factors. Although influential, these factors are largely static or beyond the influence of educators and schools (e.g., socio-economic background; Anderson & Keith, 1997). More fruitful avenues of research and practice include malleable microsystemic environmental factors. Of these, teachers are most proximal to student learning and have been found to exert the greatest influence on student engagement and corresponding achievement (Durksen et al., 2017; Hill & Rowe, 1996; Hattie, 2008).

Teachers' Influence on Engagement

Teachers play an important role in engaging students not just in the classroom but in their broader educational experience. Yet, teachers are a heterogeneous group; they vary in their knowledge, beliefs, attitudes, and instructional practices that influence student academic and behavioral outcomes. Considerable research has investigated what teacher-level factors or characteristics impact student engagement. Some of this work has consistently linked specific teacher behaviors to student engagement and motivation (e.g., Skinner & Belmont, 1993). A complimentary body of work has focused on how teacher self-perceptions and their perceptions of students impact student outcomes such as grades (Caprara, Barbaranelli, Steca, & Malone, 2006; Alvidrez & Weinstein, 1999). These two literatures differ in the collective perceived importance of external and internal teacher characteristics as meaningful determinants of student outcomes. As such, they are rarely integrated theoretically and empirically, despite the potential for integration to reveal meaningful dynamics between teacher perceptions and their behaviors. This study was one of few to combine these perspectives. Key factors from each perspective were tested for their relationship to student engagement and math achievement while controlling for the presence of each other.

The behavioral approach to educational research emphasizes the objective and observable behaviors of teachers that affect student engagement (Skinner & Belmont, 1993). According to this perspective, certain behaviors (e.g., antecedent, teaching and consequent) promote student engagement while others lessen engagement (Shernoff, Csikszentmihalyi, Schneider, & Shernoff, 2014). Behaviors that promote math engagement include effective instructional practices such as cooperative learning,

dialogues, authentic activities, cognitive strategy instruction, feedback and evaluation, and goal setting (Finn, 1989; Skinner & Belmont, 1993). Survey results from the 2015 Trends in International Mathematics and Science Study (Mullis, Martin, Foy, & Hooper, 2016) indicated that 68% of upper elementary students worldwide reported their teacher instructed in a way that engaged them in their math work. This resulted in demonstrable differences in average math achievement. Other influential teacher behaviors include interpersonal interactions (e.g., Connell & Wellborn, 1991; Teven & McCroskey, 1997) and student autonomy support (Flink, Boggiano, & Barrett, 1990). Given the link between engagement and student outcomes, teacher behaviors indirectly impact student performance in the classroom by way of engagement.

As mentioned above, effective instructional practices can result in increased student engagement. Within mathematics, there are several evidence-based effective instructional practices that improve student mathematics achievement (Chard, Ketterlin-Geller, Jungjohann, & Baker, 2009; Gersten et al., 2009). Many of these fall under the explicit instruction pedagogy emphasizing direct modeling of skills and behaviors and scaffolded activities that allow students to demonstrate mastery of concrete mathematical concepts and procedures (Kroesbergen, Van Luit, & Maas, 2004; Poncy, McCallum, & Schmitt, 2010). Although effective for achievement, less is known about how these practices also promote student engagement. One hypothesized pathway is that student engagement partially mediates the relationship between effective instruction and math achievement. That is, these instructional practices promote math achievement by keeping students focused and on-task (i.e., behaviorally engaged), with material that captures students' interest in mathematical concepts or encourages perseverance needed to

develop robust mathematical skills (i.e., cognitively engaged), and improving student-teacher interactions (i.e., affective engagement). This relationship has not been well researched, however, and particularly less so when examining specific instructional practices. Cognitive strategy instruction and use (Wolters & Pintrich, 1998) and mastery-oriented goal setting (Bong, 2009) are two observable instructional practices with demonstrated positive impacts on student engagement and performance within mathematics. Several effective math instructional strategies exist (i.e., explicit instruction, peer tutoring, sequenced instruction, use of heuristics, use of manipulatives and visual aids, verbalization or “think alouds”, consistent feedback and progress monitoring; Gersten et al., 2009) that have not been explicitly linked to engagement.

In contrast to observable teacher behaviors, other researchers have emphasized internal, subjective qualities such as attributions, beliefs and attitudes, job satisfaction, and similar characteristics on student engagement and achievement (Martin, Sass, & Schmitt, 2012; Polly et al., 2013). Their body of work draws from psychological theories to determine what characteristics to explore and infer how they influence student engagement and achievement. One prominent theory is social-cognitive theory (SCT; see Bandura, 2001), which states that an individual’s behavior is informed by their self-perceptions, their perceptions of their context and norms within that context, and their capacity to regulate emotions and thoughts. Self-efficacy is the most salient construct derived from SCT, with extensive research examining the relationship between teacher self-efficacy and student engagement and achievement (Guo, Connor, Yang, Roehrig, & Morrison, 2012; Midgley, Feldlaufer, & Eccles, 1989). Self-efficacy’s predictive power and its malleability make it a critical factor in instruction. According to Bandura (2001), a

teacher's self-efficacy is informed by experiences and personal feedback that informs their analysis and interpretation of a task (i.e., teaching math), contrasting it with their perceived competence with the task. This leads to internal positive or negative self-evaluations of achievable goals, the degree of effort they can direct toward the task, and the extent of their resiliency. A teacher with high self-efficacy would more likely engage in positive instructional and relational behaviors than their peers with low self-efficacy, as well as be more committed and innovative. As a result, their students would be more likely to be engaged with their material and achieve more, leading to a feedback loop for teachers. Indeed, research supports this relationship (e.g., Martin, 2006; Midgley, Feldlaufer, & Eccles, 1989), warranting self-efficacy as a construct worth accounting for when examining how teachers influence students. However, there is some disagreement among researchers about the relative importance of self-efficacy over instructional practices (Mujis & Reynolds, 2002). The evidence is inconclusive, and further research is needed to examine whether teacher self-efficacy or enhancing instructional practices has a stronger association with student engagement and math achievement.

As work within social-cognitive theory has advanced, psychologists and educators have expanded the array of constructs that potentially fall under its domain. For example, growth mindset (Dweck, 2006) has experienced a surge in research and popular interest over the last decade (Boaler, 2013). Growth mindset is an internal set of beliefs and assumptions about the malleability of intelligence and abilities. While growth mindset has been thoroughly examined among students, only recently has it been studied within teachers. Moreover, it has rarely been studied in relation to other teacher beliefs or instructional practices. More research is needed to determine whether growth mindset

influences student engagement and math achievement above and beyond self-efficacy and instructional practices.

Teachers' Implicit Theories of Intelligence

People may hold implicit, or unconscious, beliefs about many things that inform their perspectives and behaviors. Implicit theories of intelligence describe an individual's assumptions about the importance and malleability of innate intellectual ability on school and life function. These assumptions place constraints around a person's attitudes toward specific behaviors related to cognitively demanding tasks and their motivation to engage in said behaviors. These behaviors include task initiation and persistence, self-regulation to check for mistakes, and incorporation of feedback to improve performance. The combination of a person's implicit theory, accompanying motivation and other attitudes, and choice behaviors describe their mindset (Dweck, 2006). Thus, implicit theories and mindsets are highly related but not synonymous. The two primary types of intelligence mindsets discussed in the literature are the fixed mindset, which is based on an entity theory that adopts a deterministic view of intelligence, and growth mindset, which is based upon an incremental theory that allows for more freedom in action and outcomes.

Most research on implicit theories of intelligence for educational outcomes have been done with students, and recent work suggests that the popularity of mindsets in education have outpaced the research (Sisk, Burgoyne, Sun, Butler, & Macnamara, 2018). The average correlation between a student's mindset and their academic achievement across several studies was .1, and there was considerable variability in this estimate. Moreover, the average treatment effect on academic achievement (Cohen's *d*)

for intervention studies with students was .08 with, again, considerable heterogeneity that was not explained by moderators including the lag between intervention implementation and post-assessment, academic domain, or the implementer (Sisk, Burgoyne, Sun, Butler, & Macnamara, 2018). Despite these findings, attention has recently shifted to teachers and how teachers' implicit theories impact instruction and student engagement. Scholars are also interested in how teacher implicit theories can be passed on to students, yet more research is warranted in this area as it currently remains inconclusive (Haimovitz & Dweck, 2017).

Researchers have drawn two critical conclusions from these initial investigations. First, many teachers profess an incremental theory of intelligence but their instruction and interactions with students do not always align with that belief. In fact, Haimovitz and Dweck (2017) argued, with preliminary empirical support, that the way teachers instruct is more relevant to student outcomes than teacher implicit theories. These findings echoed Mujis and Reynolds (2002) that instructional practices were a better predictor of student engagement than self-efficacy. These findings need to be replicated.

The second conclusion is that a teacher's general implicit theory of intelligence may be less important than the implicit theory about their students specifically. That is, what teachers *expect of the intellectually abilities of their students* may be more important than their expectations about general human intelligence. Jussim and Harber (2005) reviewed 40 years of research on how teacher expectations impact classroom proceedings and student outcomes. They found that teacher expectations, or their beliefs about their students, were predictive of student outcomes. Some research indicated disparities between student and teacher racial/ethnic identification and the expectations

placed on students resulting from these disparities were exceptionally predictive of outcomes (Farkas, 2003). The exact causal mechanism(s) connecting teacher expectations to student outcomes is unclear. One notable candidate is the self-fulfilling prophecy (Brophy, 1983) in which students begin to implicitly or explicitly adopt the expectations of their teacher (regardless of the positivity or veracity of those expectations). Thus, if students perceive that their teacher expects them to remain fixed in their abilities, students may behave in ways that realize those expectations.

Teacher expectations may be conveyed through student-teacher interactions, teacher verbal behavior, or teacher instructional behavior (Brophy & Good, 1970). Importantly, since these beliefs are considered implicit, teachers may be unaware of how their own expectations manifest and influence students. Likewise, students may be unaware of these expectations being placed on them but may still respond accordingly. For example, Haimovitz and Dweck (2017) demonstrated that teachers with an entity theory and who expect their students to remain fixed in their intellectual ability adopt instructional practices emphasizing summative performance, competition, and demonstrations of skill over progress. These types of instructional practice reflect a performance-oriented instructional pedagogy (Anderman et al., 2001) and their students adopted a similar performance-orientation. The reverse was true. Teachers with an incremental theory, who expected their students to be able to improve, employed mastery-oriented instructional practices that emphasized growth and task mastery; their students adopted a similar mastery orientation. Previous work has demonstrated that students with a performance orientation tend to be more academically engaged than mastery-oriented peers, but less so in other domains of student engagement (Handelsman,

Briggs, Sullivan, & Towler, 2005). Thus, from a SCT perspective, altering a teacher's implicit theory about their students' math intelligence may change their expectations of their students' math abilities, their instructional practices, and ultimately student engagement.

Teacher implicit theories in math. In her popular book, Dweck (2006) stressed the importance that implicit theories are not universal within a person. It is possible to be oriented toward growth in one aspect of life and be oriented toward stasis in another. The same could be said for self-efficacy and other social-cognitive characteristics; because SCT posits that people's thoughts and behaviors are context-specific, research should consider context over broad generalizations. Research into implicit theories can often overlook this critical component and instead measure general outcomes such as GPA. This has been particularly true in intervention research attempting to change implicit theories in students (e.g., Blackwell, Trzesniewski, & Dweck, 2007). Yet, some work within implicit theories has investigated the construct's utility within narrow domains.

Specifically, student engagement in mathematics is a domain that has received considerable attention within the mindset research field (for a summary, see Dweck, 2014a). Fixed mindsets derived from implicit entity theories emphasize natural mathematic capability (i.e., being a "math person") and are, anecdotally, pervasive in the American population. A common fixed-mindset belief is that if a student struggles it must be because they are not mathematically gifted. Therefore, students with a history of math difficulties may be more inclined to adopt an entity theory and disengage in their work. Fortunately, intervention research has so far demonstrated that even students late in their education careers (i.e., secondary students) with a history of mathematic struggles can

make meaningful gains in performance when effectively taught (Jitendra et al., 2018). In other words, research suggests that effective instruction is critical for student success in math, yet the implementation of effective instructional practices appears highly related to a teacher's implicit theory of intelligence (Haimovitz & Dweck, 2017).

Rationale and Purpose of this Study: What Matters More, Instruction or Teacher Beliefs?

Although sometimes proposed in the literature (e.g., Mujis & Reynolds, 2002), rarely are teacher beliefs and instructional practices considered simultaneously. More specifically, self-efficacy beliefs and instructional practices have received some attention in the literature, but this work is lacking in quantity and quality to form the foundation of any solid conclusions about which is most critical or how they interact. In addition, the popularity of growth mindset warrants further investigation as it has been rarely studied in teachers and not alongside the more established constructs of self-efficacy and math instructional effectiveness. Only two studies have looked at the relationship between implicit theories and instructional practices (Haimovitz & Dweck, 2017; Park, Gunderson, Tsukayama, Levine, & Beilock, 2016). Further work is needed to bridge teacher self-efficacy, their implicit theories, their instructional practices, and the engagement and achievement of their students within mathematics.

The purpose of this study was to empirically examine how teacher beliefs and self-reported instructional practices influence student engagement and math achievement. Specifically, this study performed structural and mixture modeling informed by theory and previous research to examine how two teacher-level social-cognitive factors—self-

efficacy and implicit theories of student math intelligence—relate to multiple domains of student engagement and math achievement. Specifically, this study had three aims. The first aim was to continue the work of Mujis and Reynolds (2002) and Park and colleagues (2016) by examining the importance of teacher self-efficacy and self-reported instructional effectiveness simultaneously instead of separately, as appears more common in the literature. The second aim was to assess the value-added of a teacher's implicit theory of intelligence, while also exploring structural models of how self-efficacy, instructional effectiveness, and implicit theory relate to one-another and student outcomes. The final aim was to explore if certain teacher subgroups, or profiles, could be determined according to their beliefs and behaviors. This final aim culminated the integration of the behavioral and social-cognitive approaches reviewed in this study to determine if there were patterns of how beliefs and behaviors interacted within people and how those patterns differentially impacted student outcomes. In line with each aim, the following research questions guided this study:

- 1) Do teacher's social-cognitive beliefs (self-efficacy and implicit theories) and self-reported math instructional effectiveness differentially relate to three factors of student engagement (affective, cognitive, and behavioral), proximally, and student math achievement, distally?
- 2) Does a teachers' self-reported instructional effectiveness mediate the relationship between their self-efficacy and implicit theory and factors of student engagement?
- 3) Can teachers reliably and validly be classified into latent profiles according to social-cognitive factors and self-reported math instructional practices, and do the

resulting latent groups differentially relate to student self-reported engagement and math achievement?

For the first research question, I hypothesized that teacher self-efficacy would present a stronger relationship to student engagement and math achievement than teacher implicit theory. Self-reported math instruction effectiveness would present the strongest relationship between all three teacher-level factors, as has been demonstrated in previous research (Mujis & Reynolds, 2002). In addition, I hypothesized that instruction effectiveness would mediate the relationship between teachers' social-cognitive beliefs, since beliefs themselves cannot directly impact students—they must be enacted. Three models were proposed to test these hypotheses. The first model (Figure 1) replicated previous research by positing teacher self-efficacy and instructional practices as exogenous variables influencing all three dimensions of student engagement as mediating variables that then lead to math achievement. This model served as a base model against which the remaining models could be compared and is referred to as the Base Model in this study.

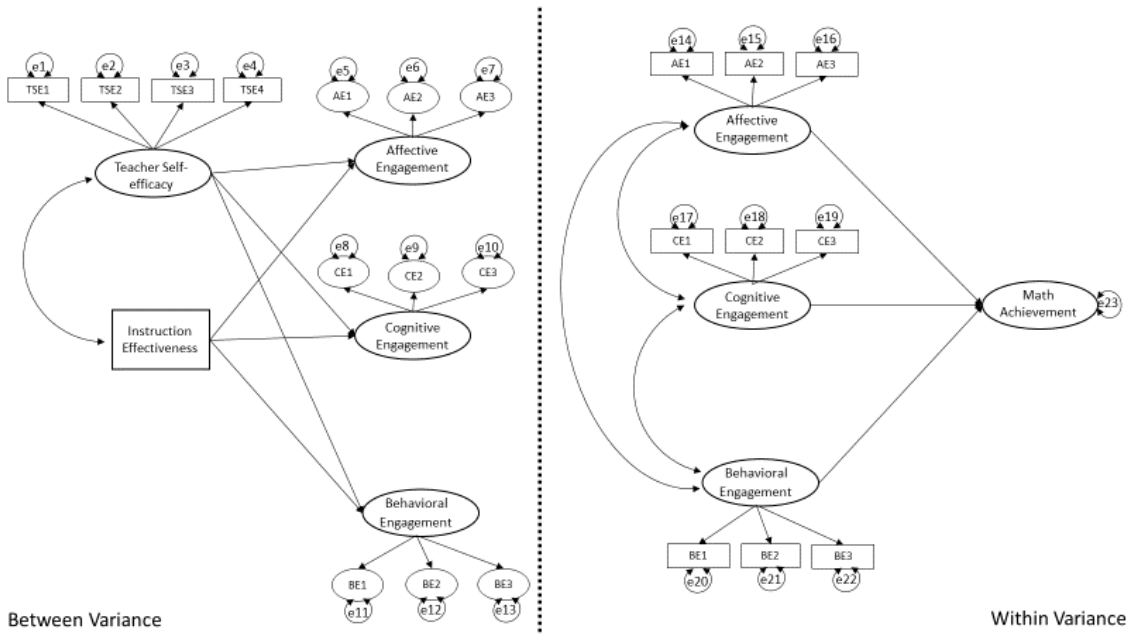


Figure 1. Base Model assessing relative importance of instruction and teacher self-efficacy on student engagement and achievement. This model was meant to replicate past findings and serve as a comparison model for future comparisons.

The second model (Figure 2) included teacher implicit theory as a correlate between teacher self-efficacy and instruction. This model, termed the Mindset Model, assessed the value added by including teacher implicit theory. It tested the partial correlation between a teacher’s implicit theory and their self-efficacy, instructional effectiveness, and direct relationship to the three student engagement dimensions.

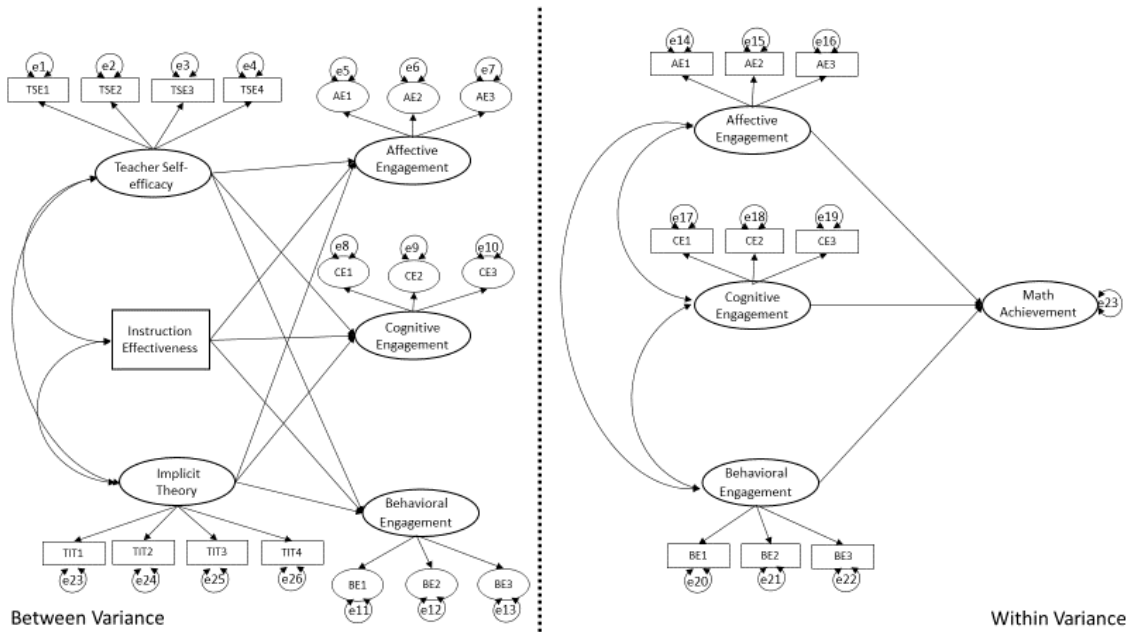


Figure 2. Mindset Model assessing the relative importance of teacher mindset on student engagement and achievement after controlling for the effect of self-efficacy and instructional effectiveness.

The final model (Figure 3) removed direct effects between teacher beliefs and student engagement and positioned instruction as a mediator between teacher beliefs and engagement. This model was termed the Mediation Model in this study and was based in the argument that self-efficacy and implicit theory would not be able to directly influence student characteristics and would have to exert their influence indirectly through their instructional practices.

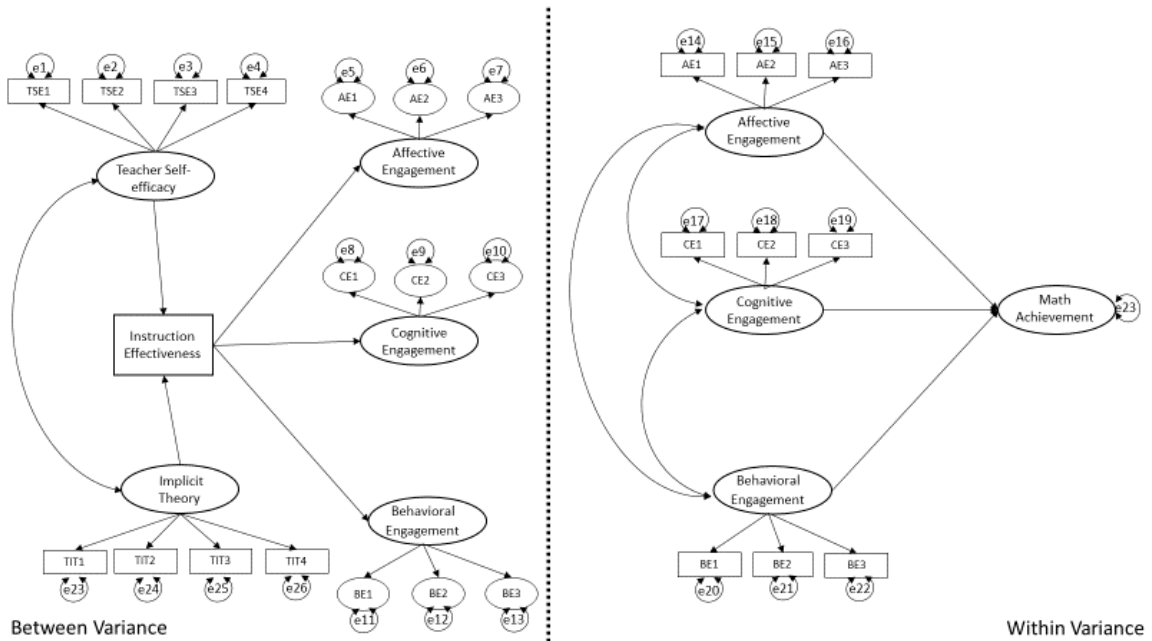


Figure 3. Mediation Model that positioned Instructional effectiveness as a mediator of teacher self-efficacy and implicit theory.

For the third research question, I hypothesized that teachers would be able to be classified reliably into six groups. Teacher self-efficacy and implicit theory were anticipated to be highly related but unique enough to provide some separation between teachers. That is, some teachers who believe they are effective teachers may be less inclined to view their instruction as a barrier for some students who struggle mathematically. This bias would lead these teachers to perceive problems with student achievement as originating in those students, i.e., a fixed mindset. Thus, teachers could be classified into congruent classes where beliefs and instruction align (low or high on all three factors) or incongruent classes (a mixture of belief and behaviors). In addition, I hypothesized teachers who are high in self-efficacy beliefs but low in effective instructional practices will have the most detrimental impacts on student engagement and achievement. This is because teachers with an inflated sense of self-efficacy may miss

opportunities to reflect on their ineffective instructional practices that hinder student engagement and mathematic competency, and iteratively improve their practices to the benefit of their students.

Chapter 2: Literature Review

Few would dispute the importance of student engagement, although some might dispute how it is conceptualized, defined and measured. Originally conceptualized more narrowly as the time a student spends on academic tasks, nearly thirty years of research have expanded engagement into a multi-dimensional construct including aspects of behavior, motivation and self-determination, after-school program participation, and executive functioning (Appleton, Christenson, & Furlong, 2008). Yet, even with its increasing definitional boundaries, one thing remains clear about student engagement: countless cross-sectional and longitudinal studies have demonstrated that increased student affective, behavioral, cognitive, and academic engagement is linked to improved school performance, high school completion and life satisfaction (for a review, see Finn & Zimmer, 2012, p.107-115). The research on student engagement is subject specific, with findings demonstrating that engagement is critical for content learning, particularly in subjects, like mathematics, that may be more challenging or students initially have less of an interest (Bodovski & Farkas, 2007). As a result, student engagement has received notable attention not just by researchers and practitioners, but also by policy makers and national organizations (National Research Council and Institute of Medicine of the National Academies, 2004).

To educational researchers and practitioners' benefit, student engagement appears to represent a multi-dimensional malleable construct amenable to intervention and prevention efforts (e.g., Bradshaw, Zmuda, Kellam, & Ialongo, 2009; Christenson, Stout, & Pohl, 2012; Gilman, Meyers, & Perez, 2004; Schunk & Mullen, 2012; Sugai & Simonsen, 2012; Thayer, Cook, Fiat, Bartlett, & Kember, in press). Research suggests

that it also is impacted by multiple levels of influence—student, home, and school—with a combination of these factors interacting together to provide the most comprehensive approach to intervention (Goldstein, Little, & Akin-Little, 2003).

Multi-level Influences on Student Performance

Education occurs in a dynamic system of overlapping and interacting factors (Bronfenbrenner, 1977). At the center of this system is the student with their own genetic makeup, beliefs, background experiences and knowledge, attitudes, and skills. Even within the education ecology, within-student variables appear to be quite important to engagement and achievement as they interact with and represent outcomes of environmental factors (Reeve, 2012). Nearly half of student achievement can be attributed to student variables including cognitive ability, their disposition and motivation to learn, their affective attributes, and even their physical aptitude (Hattie, 2008). This leaves half of the variance in student outcomes being explained by other contextual factors of the school environment (e.g., classroom structure, school climate, policies and procedures, quality of student-teacher relationships and interactions), home environment (e.g., number of caregivers, inner-family conflicts, shelter security and mobility, social-economic factors), and interactions between these factors (e.g., parent-teacher trust and involvement; Froiland & Davison, 2014; Goldstein, Little, & Akin-Little, 2003). From an intervention and prevention perspective, these external contextual influences are critical because many of them, such as the quality of student-teacher interactions, are under the control of educators, whereas other factors like negative past school experiences or risk factors outside of the school (e.g., single parent household) that contribute to student disengagement are not. Due to the broad definition of engagement that includes

cognitive, affective, and behavioral dimensions, the number of pinpoints for intervention that are under the control of educators has also expanded. Although there are several important factors, there is a need to narrow the focus on factors to those that are most proximal to student engagement and performance and represent feasible, malleable targets for intervention, such as teachers. This is particularly true in the area of mathematics where poverty, parental involvement and expectations, and other distal factors (i.e., less malleable factors or beyond the control of educators) have been directly associated with math performance, although their influence can be attenuated indirectly through opportunity (e.g., quality of instruction) and propensity factors (e.g., math engagement; Byrnes & Miller, 2007).

Teachers Are Proximal Social Actors

Classrooms are inherently social environments that involve daily reciprocal interactions between a teacher and students. Teacher-student interactions help shape and mold classroom performance (Brophy and Good, 1970). And, as the classroom's main social agents of change (Bandura, 1969), what teachers believe, say, and do may directly and indirectly influence student perceptions of themselves, feelings towards school, and classroom behavior (e.g., Skinner & Belmont, 1993). Teachers wield significant influence over the development of their students with an estimated 30% of variability in student achievement explained by teacher-level factors (Hattie, 2008). No other studied variable, beyond the student themselves, accounts for this much variance in student outcomes nor serves as an intervention target proximal to student engagement.

Research has consistently explored how teachers impact student motivation and engagement and which factors appear to be most influential. For example, researchers

investigated the reciprocal relationship between how much structure and support a teacher provided their students and their students' perception of their own engagement in the classroom (Skinner & Belmont, 1993). Statistically significant, moderate relationships were found, with some of the strongest associations found between how students' perceived their teacher's actions and their own classroom engagement. In an extension on this study, other researchers examined student engagement from an ecological and developmental perspective (You & Sharkey, 2009) and determined that student and their teachers were the primary factors in the student's engagement over time. However, in both these studies, teachers themselves were not directly investigated. These studies examined important variables like classroom structure and each teacher's years of teaching experience, evidencing that factors at the teacher-level are associated with student engagement. But specific teacher beliefs and behaviors were not considered.

Teacher-level factors are frequently conceptualized and approached by researchers and practitioners from two primary theoretical perspectives. The first stems from a psychological, social-cognitive perspective, which entails examining internal, subjective beliefs and characteristics (e.g., self-efficacy) hypothesized to influence student outcomes (e.g., Caprara, Barbaranelli, Steca, & Malone, 2006). The second represents a behavioral perspective which examines external, objective, observable behaviors linked to promoting low-inference indicators of student outcomes (e.g., Skinner & Belmont, 1993). Both have theoretical and empirical support but potentially result in different practice and policy recommendations. Moreover, the two theoretical paradigms are not mutually exclusive yet often are used to conceptualize and execute research separate from one another.

Teachers' Own Social-Cognitive Characteristics

Teachers are human beings and thus capable of holding many beliefs and perceptions about themselves, their school setting and their students. A number of theories and perspectives exist that describe and organize these beliefs, and posit how they might impact an individual. Social-cognitive theory (SCT) focuses on an individual's agency within a social environment. Agency is informed by the beliefs the individual has regarding their character, their perception of social context and norms, and their own capacity to regulate thoughts and emotions that results from the interaction between themselves and the environment (Bandura, 2001). These beliefs are referred to as social-cognitive characteristics. People have many social-cognitive characteristics, with the most prominent and researched characteristic being self-efficacy (Stajkovic & Luthans, 1998). Other important characteristics include self-regulation (Bandura, 1991), relational affect (Andersen & Chen, 2002) and motivation and related constructs (Stajkovic & Luthans, 1998). These internal, social-cognitive characteristics inform an individual's decision-making and their interactions with their environment. Thus, SCT is quite relevant and useful for explaining how teachers, as social agents, influence student engagement. This departs from a low-inference, behavioral perspective that emphasizes the acquisition and use of specific behaviors without consideration for internal factors.

Teachers possess internal characteristics that have been linked to student-level outcomes, including beliefs about themselves (e.g., self-efficacy; Caprara, Barbaranelli, Steca, & Malone, 2006) and perceptions about students within the context of the classroom (e.g., self-fulfilling prophecy, Jussim & Harber, 2005). Moreover, it has been hypothesized that these characteristics can be transferred from teacher to student through

teacher behaviors modeled in their classroom, their interactions with students with regard to what they say and do, and the adoption and delivery of effective instructional practices. Teacher self-efficacy is one of the most well-established social-cognitive characteristics.

Teacher self-efficacy. In a study examining students' mathematical beliefs as they transitioned from middle school to junior high (Midgley, Feldlaufer, & Eccles, 1989), researchers measured through self-report questionnaires teacher ($n=141$) self-efficacy and student ($n=1,329$) self-efficacy to capture perceptions of current and past mathematical performance and mathematics' difficulty relative to other students and subject areas. Teachers were categorized with either low or high self-efficacy based on their responses. Using data across four semesters, the researchers uncovered many noticeable patterns between student and teacher self-efficacy. First, student and teacher self-efficacy were highly related prior to transitioning, even after controlling for prior achievement on a statewide standardized mathematics exam. After transitioning, all students reported decreases in their perceived performance and expectations for performance in math and increases in the perceived difficulty of math tasks as semesters passed. However, students that transferred from a high efficacy teacher to a low efficacy teacher reported the greatest decrease in their perceived performance in class, their expectations for their success, and the greatest increase in their perceptions of the relative difficulty of the math content, even compared to students who were originally with a low efficacy teacher and transferred to another low efficacy teacher. This effect was more pronounced for students who were initially low achieving on the state math exam. Students originally with a low efficacy teacher and transitioned to a high efficacy teacher experienced what might be considered a protective effect as they reported decreases in

perceived performance and expectations comparable to students with high efficacy teachers pre-and post-transition (who reported the slowest decline), and had stable perceptions of relative difficulty alongside their pre-and-post transition high teacher efficacy peers. Overall, the students' beliefs and characteristics molded to resemble their teacher's beliefs and characteristics and this transfer seemingly occurred quickly (within the first semester after transitioning). This resulted in significant shifts in the students when this teacher-to-student transfer countered the student's previously held belief about themselves (i.e., low efficacy student with high efficacy teacher and high efficacy student with low efficacy teacher). Importantly, this shift was more impactful for students who were already performing low mathematically, and for those transferring from a high efficacy teacher to a low efficacy teacher, resulted in the most detrimental outcomes. These findings indicated that current student performance and attributes are best predicted by their current teacher's characteristics and not necessarily their past teacher(s). This is likely because children are engaged in a rapid development of identity, particularly during adolescence, and are susceptible to immediate social influences and rapid shifts in their perspectives. Ideally, then, students would always have a teacher with high self-efficacy because future performance may decrease in the context of a teacher with low self-efficacy.

A few studies have resulted in similar findings regarding the influence of teacher self-efficacy on student outcomes. Caprara, Barbaranelli, Steca and Malone (2006) investigated the effect of teacher self-efficacy and job satisfaction on student grades and found that, controlling for prior achievement, teacher self-efficacy was significantly and meaningfully related to job satisfaction ($\beta=.53$) and both self-efficacy and satisfaction

significantly impacted student grades ($R^2=.48$). In another study, collective teacher self-efficacy—the overall efficacy of a community of teachers within a school—was demonstrated to be a mediating variable between principal leadership and student academic achievement (Ross & Gray, 2006). The importance of self-efficacy is even evident across cultures; greater personal self-efficacy in Iranian teachers positively correlated with student intrinsic motivation ($r=.39$), disposition towards learning ($r=.79$), and there were significant differences in student achievement between groups of teachers classified as low, medium, and high efficacy (Mojavezi & Tamiz, 2012).

From these studies, self-efficacy appears to be a critical factor that influences student engagement and performance and represents a potential malleable construct amenable to intervention. However, research investigating critical teacher characteristics that impact student learning needs to continue to evolve in order to generate not just better theory but also real world applications of these concepts. For example, other potentially malleable teacher-level social-cognitive constructs gaining popularity among researchers and the press should be included in models of student and teacher characteristics to determine their relative importance. Implicit theories of intelligence, for example, which has been more heavily studied in students, is gaining popularity with regard to teachers and should be explored to determine its link to student engagement and whether it is a potentially high-yield target for intervention (e.g., Dweck, 2014).

Teacher implicit theories of student intelligence. Implicit theories of intelligence were first officially introduced into the popular education and psychology vernacular over a decade ago (Dweck, 2006). These constructs—best considered two extremes of a bidirectional construct—emerged from converging research beginning with

learned optimism and task persistence (Peltier, Laden, & Matranga, 2000; Dweck & Leggett, 1988; Leggett, 1985). As people develop they form beliefs and assumptions about the importance of intelligence, its origin, and its malleability. These beliefs and assumptions generally culminate in two theories about the reality of intelligence: entity and incremental. Entity theory posits that intelligence is static and predetermined. In contrast, an incremental theory posits that intelligence develops incrementally from experiences. From these theories, individuals derive their orientation toward achievement. Either they adopt a fixed mindset (i.e., their intelligence, and other traits, are fixed and are the primary determinants of success) or growth mindset (i.e., personal traits are developed over time with effort and learning the determinants of success; Dweck, 2006).

Growth mindset¹ is a positive belief about ability, talents, and development that influences other self-concept beliefs and behaviors. Thus, it can be measured proximally through self-report measures and distally through association with response outcomes like academic achievement, persistence, and various dimensions of motivation. Indeed, correlational research has linked student mindset to math performance (Blackwell, Trzesniewski, & Dweck, 2007), statistics performance (Aditomo, 2015), performance chemistry courses (Grant & Dweck, 2003), psychological well-being and school engagement (Zeng, Hou, & Peng, 2016), self-regulation (Burnette, O'boyle, VanEpps, Pollack, & Finkel, 2013), changes in academic motivation (Haimovitz, Wormington, & Corpus, 2011), to name a few examples. Experimental research has linked changes in

¹ For the purposes of this paper, mindsets and implicit theories may be used interchangeably.

mindset to broadly academic achievement (Blackwell, Trzesniewski, & Dweck, 2007; Yeager et al., 2016), science performance (Esparza, Shumow, & Schmidt, 2014), remediation of students at-risk for dropout (Paunesku et al., 2015), and reading and math achievement (Good, Aronson, & Inzlicht, 2003). Given the preponderance of evidence, the relationship between these variables for students is apparent.

Yet, so far, the research on *teacher* implicit theories is limited, in general, and results from scant investigations into how teacher implicit theories impact student characteristics is inconclusive. One study investigated the relationship between implicit theories of postsecondary instructors and several student outcomes including academic and perceptions (Rattan, Good, & Dweck, 2012). Results indicated that instructor mindset was related to many of these outcomes. Another study directly investigated how teacher mindset impacts primary students' mindsets (Park, Gunderson, Tsukayama, Levine, & Beilock, 2016). The researchers measured both student and teacher motivational frameworks (which encompasses implicit theories) as well as conducted instruction and classroom behaviors. Mixed-effects models were used to assess the relationship between these variables and other related covariates. In general, they discovered that student motivational framework predicted end-of-year math achievement and that instructional practices, dichotomized as performance-oriented or mastery-oriented, predicted student achievement and motivational. Instructor mindset, however, did not contribute any explanatory power to their models, leaving in question the utility of this construct. Others, however, continue to express the potential promise of studying teacher mindsets in relation to student outcomes (Haimovitz & Dweck, 2017).

A unique aspect of teacher mindset that has not yet been studied is the target of

the mindset belief (e.g., self or other). Although the typical definition of a growth mindset incorporates an individual's perceptions about themselves (Dweck, 2006) and the subsequent effects that mindset has on their own behavior, the construct can generalize beyond the self. A person could potentially have a mindset belief about others that influences their behavior while their beliefs of others may be related but different. In other words, teachers may have unique implicit beliefs about their students' intelligence and capacity for growth. These beliefs can have meaningful impacts on student outcomes. In a review of nearly 40 years of research into the effects of teacher expectations on classroom proceedings and student outcomes, teacher expectations, or their beliefs about their students, were determined to be predictive of student outcomes (Jussim & Harber, 2005), particularly in recent research into disparities between student and teacher racial/ethnic identification and the accompanying expectations (Farkas, 2003). If a teacher expects students to be unable to develop, their behaviors may align.

Research into teacher implicit theories and other relevant characteristics is warranted, especially if future research determines them to not only be key causal factors of student engagement but are also malleable to low-cost, efficient interventions. Simultaneously, though, researchers need to be cautious as they pursue this research line. Despite strong correlational evidence for the relationship between teacher characteristics and student characteristics and outcomes, researchers should consider whether targeting these characteristics is as equally or more beneficial than improving other aspects of the student-teacher relationship.

Interplay between Classroom Practices and Social-cognitive Characteristics

Teacher characteristics may shape student engagement but they are indirect; their

effects have to be mediated by more proximal factors such as how and what teacher's communicate to students (e.g., positively greeting students, Cook et al., 2017) or the instructional practices they incorporate into routine classroom delivery (e.g., opportunities to respond, Lambert, Cartledge, Heward, & Lo, 2006). The logic behind research and practice emphasizing these characteristics assumes that positively changing internal perceptions and beliefs results in a cascade of effects that influences teacher behavior including instruction, student-teacher interactions, and other character traits (see Figure 4). These behaviors, in turn, reinforce those social-cognitive characteristics.

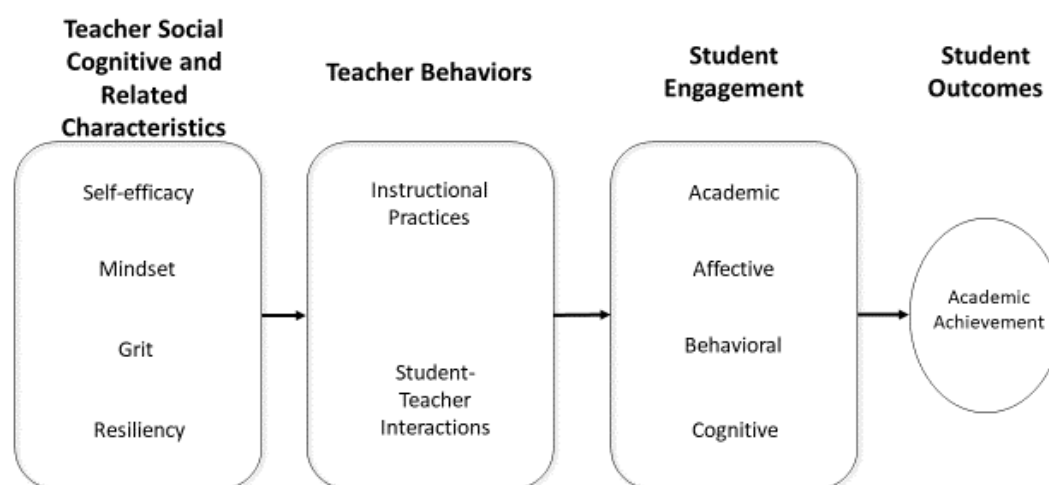


Figure 4. Social-cognitive characteristics indirectly influence student outcomes by changing teacher behaviors. It is hypothesized that changes in these characteristics will cascade through the model at every point.

From a behavioral perspective, it may be more effective to target desired classroom behaviors teachers exhibit to promote student engagement. Research into effective teaching using a behavioral approach tends to emphasize low-inference, or observable and directly-related, factors in lieu of unobservable, latent traits that are difficult to

measure and must exert their influence indirectly through other traits and behaviors (e.g., Land, 1979; Murray, 1983). These observable factors are often very specifically defined behaviors and measured through observational methods. In direct contrast to a social-cognitive approach, Mujis and Reynolds (2002) questioned what truly mattered when it came to improving student math outcomes: what teacher's believe or how they behave in the classroom. After measuring teacher self-efficacy and content knowledge, they determined that proximal factors like teacher behaviors and practices were more influential than internal factors like teacher beliefs, although beliefs were still relevant. A limitation of this study is the researchers did not directly test the mediation between characteristics and behaviors but the results still suggested that, if forced to select only one of the approaches, teacher behaviors and practices may be the more important one.

This focus on instructional practices has recently been adopted within the nascent research efforts into teacher mindset. In a recent article, prominent growth mindset researchers reviewed a portion of the current literature on the origin of student mindsets (Haimovitz & Dweck, 2017). They determined that student mindsets are socially informed from a student's peers and teacher. Based on results from a small collection of studies, they posited that teachers who adopt a growth mindset were more likely to have a process-focused learning orientation towards student successes and failures which is predicted to instill a growth mindset in their students and bolster other student self-beliefs (e.g., efficacy, motivation, engagement). Process-focused learning orientation includes practices that emphasized deep, conceptual learning; student explanation of their problem-solving processes; consistent and specific feedback; revision of work and judicious review of progress; and verbal explanations of struggles as a normal process of

learning (Haimovitz & Dweck, 2017). These instructional practices resemble general universal and targeted evidence-based instructional practices across academic domains. For example, the National Research Council identified each of these as evidence-based practices for tier 2 mathematics (see Gersten et al., 2009, p.1210) and recommended that teachers incorporate them into their whole class instruction when needed and deemed appropriate. Considering that over 60% of 4th, 8th, and 12th grade U.S. students perform below proficiency on national (e.g., National Center for Education Statistics, 2015) and international standardized math tests (Kastberg, Chan, and Murray, 2016), and in a recent sample of 1st-3rd grade students, only an estimated 36% demonstrated automaticity with basic math facts (Stickney, Sharp, & Kenyon, 2012), suggesting that instilling a growth mindset and process-focused instructional practices may be critical to bolster national math competency.

Thus, although teacher mindsets may be related to student performance, the instructional strategies teachers use may exert the most influence on student engagement. Indeed, two social psychology researchers who investigate growth mindset warn against diverting time and resources away from implementing quality instructional practices in favor of social-psychological interventions (in which mindset interventions can be categorized) to build student qualities:

“Social-psychological interventions complement—and do not replace—traditional educational reforms. They do not teach students academic content or skills, restructure schools, or improve teacher training. Instead, they allow students to take better advantage of learning opportunities that are present in schools and tap into existing recursive processes to generate long-lasting effects,” (Yeager & Walton, 2011, p.293).

There are clear theoretical reasons and real-world consequences for why instructional practices are likely the ultimate determinant of student engagement and achievement. Teacher social-cognitive characteristics inform or increase the probability of certain behaviors but they do not guarantee behaviors. According to the Theory of Planned Behavior (TPB; Ajzen, 1991), behavior is best predicted by behavioral intentions. Intentions, in turn, are informed by social-cognitive and environmental factors including self-efficacy, perceived social norms, motivation to comply with norms, the expected reality and value of the intended behavior outcomes, and, although not included in the traditional TPB model, an individual's mindset beliefs related to students' ability to grow and develop talents. In simpler words, what an individual thinks about themselves and their social environment influences their intentions to engage in a behavior but does not guarantee the behavior (Armitage & Conner, 2001). Within teachers, beliefs are important but the most influential teacher characteristics are the behavior they exhibit, including how they teach.

TPB also suggests that what an individual intends to do and what they actually do are not always congruent because behavior is ultimately probable. In one meta-analysis on the predictive accuracy of attitudes, norms, and perceived behavioral control measures in studies using TPB as a theoretical orientation determined that these components explained approximately 41-50% of variability in measures of intention which, in turn, accounted for 27% of variance in behavior outcomes (Armitage & Conner, 2001) For teachers, that means that what a teacher believes about themselves and their students may lead them to develop particular intentions that are not behaviorally realized. A teacher with high perceived self-efficacy may still not implement effective practices or do so

with high competence. A teacher that believes in the malleability of their students' intelligence and skills may still fail to structure the educational environment that affords the development of that intelligence and skillset. In general, students may receive one message from their teachers (e.g., "You can succeed if you practice and work hard") but the instruction they receive does not help them actualize that message. This incongruence can have negative consequences for student engagement and achievement, such as disengagement from school from a lack of success experiences and distrust in teacher efficacy.

In fact, this congruence/incongruence dichotomy is why a behavioral approach alone is inadequate in some contexts to explain how teachers influence student engagement and offer practitioners intervention points. It provides a narrow list of explanations for why some teachers implement effective instructional practices and others do not. For some teachers, the environmental antecedent (e.g. motivating operators) and consequent (e.g., salient reinforcement) stimuli support implementation. For others, social-cognitive characteristics may represent importance antecedents necessary for successful adoption and implementation of effective instructional practices in addition to environmental stimuli.

An approach that integrates social-cognitive perspective and behavioral perspectives, if founded on clear linkages between characteristics and behaviors, is likely to provide a more comprehensive account of teacher-level factors that influence student engagement and provide multiple entry points for intervention. There may be cases where teacher self-efficacy or mindset, despite being latent traits with indirect effects, are the principal explanatory variables and intervention targets for student engagement and

achievement. In other cases, instructional practices are principal. But characteristics and practices need to be explored simultaneously to determine if such an integrative approach is valid and useful. Given the context of exploring variables tapping the constructs of interest and teachers themselves, this integrated approach could be conducted from two related analytic approaches—the traditional variable-centered approach and the more contemporary person-centered approach.

Pros and Cons of Variable- and Person-centered Analytic Methods

The “variable” versus “person” language traces back to Block (1971) who recognized the limitations of examining relationships among variables alone. Researchers are often interested in understanding the importance of particular constructs or variables. Fundamentally, variable-centered analyses consider how characteristics are related to each other. Within applied research, a variable-centered approach places a focus on examining treatment conditions and modalities, predictor variables, demographic covariates, and potential confound factors. Analysis of variance, regression, factor analysis, and related multivariate techniques are the tools of choice when parsing variances related to each variable to determine their association with or contributions to some outcome(s). These methods help guide researchers into pursuing meaningful variables and develop useful applications for manipulating these variables for prosocial outcomes. However, researchers must be careful because these methods do not determine absolute variable significance. A variable’s significance is attenuated by the presence or lack of presence of other variables in a model; hence the need for integrated models that compare key explanatory variables from different perspectives and research lines. In addition, these methods can obscure patterns between these variables that may be just as,

if not more, important as the variables themselves (Magnusson, 1998). Interaction terms capture some of these relationships but interpretation can be difficult, particularly as the number of interacted variables increases.

Unlike variable-centered analyses, person-centered analyses examine how variables group or cluster within individuals (Magnusson, 1998). In contrast, psychologists may be more interested in how variables configure to characterize homogenous groups of individuals. By using statistical clustering techniques and decision guidelines, researchers can identify configurations of variables and how they classify different groups individuals according to variables included in a model. A unique benefit of this approach is it allows researchers to provide prevalence estimates for the various groups that form a sample, while simultaneously providing an empirical foundation for testing group differences. However, clustering techniques could be considered arbitrary in that clusters can be formed to fit to any sample, although fit may not be ideal. Thus, the groups are highly susceptible to sample idiosyncrasies and suffer external validity challenges (Murdock & Miller, 2003).

These methods are not exclusive to one another and have been employed in the same studies to address different research questions in fields such as public health (Murdock & Miller, 2003). A variable-centered approach can be used first to determine variables with empirical support for their association for some outcome, and then a person-centered approach with the empirically supported variables used to determine groups. These groups would need to be validated for validity with other measures and then can be used again in a variable-centered approach to determine differences between groups.

Summary of Literature Review

Engagement is a critical factor in student success and development because it functions as a malleable protective factor countering static risk factors for student dropout and subsequent negative impacts of life satisfaction and quality (Finn & Zimmer, 2012). Among the myriad of environmental factors influencing student engagement, teachers are a highly proximal and prominent factor (Hattie, 2008). Students interact with them for extended periods of time, multiple times throughout a week. And since classrooms are highly social environments, teachers are continuously modeling and shaping behavior, skills, and engagement. They do this through a variety of student-teacher interactions including the instructional practices teachers use (Kunter, Klusmann, Baumert, Richter, Voss, & Hachfeld, 2013). Yet, teachers are also influenced by the social environment and their behaviors are potentially influenced by social-cognitive beliefs teachers hold. Their implementation of effective instructional practices that develop student engagement and improve achievement may be dependent upon their belief in their own capability to teach their students (i.e., self-efficacy; Mojavezi & Tamiz, 2012) and the capacity of their students to learn new knowledge and skills (i.e., student-focused mindset; Haimovitz & Dweck, 2017; Jussim & Harber, 2005). Until recently (e.g., Kunter, Klusmann, Baumert, Richter, Voss, & Hachfeld, 2013; Martin, 2006), research into how teachers' instructional practices and social-cognitive beliefs has largely been conducted in isolation, with little integration. This precludes understanding the relative importance of these teacher characteristics as well as understanding how they might influence and interact with each other.

An integrative approach in this field offers several benefits. First, it illuminates the complimentary nature between behavioral and social-cognitive perspectives on student-teacher interactions. Second, it allows for value-added research to explore additional variables potentially related to student engagement. Several instructional practices and social-cognitive beliefs may be independently related to student engagement but less so in the presence of other teacher characteristics. Third, it allows for the classification of teachers along multiple dimensions to determine how the interactions between instruction and social-cognitive beliefs impact student engagement. Finally, integrated research provides practitioners several intervention points and a broader perspective to use when selecting said intervention points. Teachers and other interventionists can better adapt their efforts to increase student engagement based on their contexts.

Chapter 3: Method

Chapter 3 provides an overview of the data source, measures, and the planned analyses.

Data Source

The analytic sample was drawn from the National Center for Teacher Effectiveness Study (NCTE). NCTE was an IES-funded study led by the Center for Education Policy Research at Harvard University with three primary goals: (1) to develop and refine psychometrically sound tools to assess teacher effectiveness in upper elementary mathematics education, (2) to investigate the impact of a myriad of putative associated factors (e.g., professional and classroom effects, teacher effects, teacher characteristics) and processes (e.g., teacher evaluation systems, application of IRT), and (3) dissemination of measures and study findings at conferences to promote new research and encourage immediate application of the measures. Given the primary purpose of the present study, NCTE was an appropriate data source for investigating teacher influences on student characteristics and performance. Pertinent to the present investigation, data include information on teachers' training, credentials, performance in college, years of experience, number of topics taught, efficacy, and instructional practices, as well as students' performance, item responses on comprehensive exams, and perceptions of their behavior, their peers' behavior, relationship with their teacher, and the appropriateness of their classroom environment. The data were made available through the Inter-university Consortium for Political and Social Research (ICPSR), an online database of data from studies conducted across various fields. Data are either publicly available for any citizen to download and use or require licensed access. ICPSR ensures that data remain secure

and confidential. Identifiable personal information is unavailable. All publicly available NCTE data across the entire duration of the NCTE study were accessed for this study.

Sampling. Data were collected, and made publicly available, for a base sample of approximately 10,350 4th and 5th grade students in 300 classrooms in 4 public school districts in 3 states across three years using a mixture of validated and prototype survey measures, observational methods, and access to extant records (per data use requirements, all student frequencies herein are rounded to the nearest 50). Data were collected in three waves from years 2010 to 2013 and are cross-sectional, although some capacity for longitudinal analysis exists for the small subset of the students who entered 4th grade either during the first or second data collection wave.

Recruitment. Districts included in the dataset represented a non-random, convenience sample based on prior relationships with the NCTE researchers. Schools were included based on several conditions: (1) leadership and teachers had to consent to video recordings of classroom instruction that would be conducted sporadically throughout the year and reviewed by several instructional consultants; (2) a minimum of two teachers per school consented to participate; (3) extant student data could be accessed; and (4) student rosters had to be randomized in the final year of the study to test how different instructional and teacher-evaluation practices influenced student characteristics and outcomes. No other design structures were imposed, and no sampling weights calculated.

Prior to the first year, teachers completed a background questionnaire recording their training and qualities of their teaching experience. At the beginning of every school year, teachers and students completed knowledge, beliefs, and attitudes measures.

Throughout the year, classroom instruction would be randomly recorded. A minimum of two instructional consultants independently reviewed each video for presence of effective instructional practices (discussed in the Measures section below). At the end of each year, teachers and students completed measures reflecting on their experience in school that year. These measures included frequency estimates of teaching practices, perceptions of student and teacher behaviors, and teacher perceptions of school organizational context. The timeline of the data collection supported their use in this study. Teacher beliefs were assessed at the beginning of the year. Since the teachers would have had little exposure to their current classroom students, these self-efficacy and implicit theory measures were likely to capture their typical belief unmoderated by their experiences with the new cohort. In addition, student perceptions were collected at the end of the year approximately at the same time as they took the achievement tests. This reduces the impact of time on study internal validity and strengthens the temporal association between self-reported measures of student engagement and their performance on the achievement tests.

Measures

The measures in this study consisted of teacher and student records, teacher and student self-report questionnaires administered in the fall and spring of each study year, and achievement tests. Only measures used in the second wave were included. The second wave was chosen because the NCTE measures (discussed below) underwent substantial revision after the first year of data collection. Specifically, some items were eliminated from the questionnaires and new ones created to better capture target constructs. Most importantly, items measuring implicit theories of intelligence were

included for teachers. Items from the self-report questionnaires were used to create teacher-level latent constructs including social-cognitive beliefs (i.e., self-efficacy and implicit beliefs of math intelligence) and instructional effectiveness. Similarly, items were selected as indicators of student affective, behavioral, and cognitive engagement. Scores on the achievement test were used as distal outcome variables. In addition, a subset of teacher background and organizational context variable was selected to assist in determining latent teacher profiles to answer research question 3. Table 1 presents all items used under their respective categories.

Table 1

Description and abbreviation used for all items

Teacher Implicit Theory of Intelligence (Mindset)	Abbreviation
Students have a certain amount of intelligence and they can't really do much to change it.	TIT1
Intelligence is something about students that they can't change very much.	TIT2
Students can learn new things, but they can't really change their basic intelligence.	TIT3
To be honest, students can't really change how intelligent they are.	TIT4
Teacher Self-Efficacy	Abbreviation
How much can you do to motivate students who show low interest in school work?	TSE1
How much can you do to help your students value learning?	TSE2
How much can you do to get students to believe they can do well in school work?	TSE3
How well can you establish a classroom management system with each group of students?	TSE4
Instructional Effectiveness	Abbreviation
Illustrate why a mathematical procedure works using concrete materials (e.g., cubes, base ten blocks, fraction strips)	--
Ask questions that help students understand why a procedure works	--
Compare different ways of solving problems	--
Assign problems to help students practice procedures for speed, accuracy, or ease of use	--

Introduce procedures through a formal presentation	--
Give tests on computational skills	--
Practice routine computation/algorithms	--
Instructional Effectiveness Index	IESum
Teacher Background and Organizational Context	Abbreviation
Counting this year, please indicate the total number of years you have taught mathematics:	EXP
Educational Experience:	
Number of undergraduate courses taken in mathematics	COURSES
Number of undergraduate courses taken in math content for teachers	CONTENT
Number of undergraduate courses taken in in methods for teaching math	METHODS
Educational attainment:	
A certificate in the teaching of elementary mathematics	CERT
A master's degree (any type)	MASTER
Student Affective Engagement	Abbreviation
I like the way my teacher treats people when they need help with math.	AE1
My teacher really cares how well I do in math.	AE2
If I am sad or angry, my teacher helps me feel better.	AE3
Student Cognitive Engagement	Abbreviation
The things we have done in math this year are interesting.	CE1
Because of this teacher, I am learning to love math.	CE2
I enjoy math class this year.	CE3
Student Behavioral Engagement	Abbreviation
My behavior in this class is good.	BE1
My behavior in this class sometimes annoys the teacher. (reverse-scored)	BE2
My behavior is a problem for this teacher in this class	BE3
Math Achievement	Abbreviation
Alternate Achievement Test	TEST

Teacher social-cognitive factors. As mentioned above, items from a self-report teacher questionnaire were used as indicators of the latent constructs used in this study.

This questionnaire was researcher-developed as part of the main purpose of the NCTE

study. A short overview of the development and exploratory analyses of the questionnaire are provided below for context before discussing the specific items used in this study.

The teacher questionnaire was constructed from a combination of items from the Mathematical Knowledge for Teaching assessment (MKT; Hill, Rowan, & Ball, 2005), the Massachusetts Test for Educator License assessment (MTEL), and items developed in accordance with other constructs of interest. Exploratory and confirmatory factor analysis determined that the MKT and MTEL items loaded onto a single factor the research team called *math knowledge* (Bacher-Hicks, Chin, Hill, & Staiger, unpublished manuscript). In addition, the developers conducted numerous factor analyses to determine the presence of additional supplemental latent constructs resulting from the additional items the researchers included (Bacher-Hicks, Chin, Hill, & Staiger, unpublished manuscript). These were completed for separate years and by grade, but also pooled to check overall consistency of outcomes. Researchers discovered constructs related to self-efficacy, use of formative assessment, teaching effort, Test Prep-Activities (i.e., did they incorporate instructional practices aligned to the test), and Test Prep-Instruction (i.e., has testing negatively impacted their instructional quality). They also explored a couple other constructs called Math Instruction Richness and Traditional Instruction, but these constructs did not consistently emerge across all three years (Bacher-Hicks, Chin, Hill, & Staiger, unpublished manuscript). The specific measures derived for this study were teachers' implicit theory of math intelligence and self-efficacy.

Teacher implicit theory of math intelligence. Four items assessing teachers' implicit theories of students' intelligence were used as indicators for the implicit theory latent construct. The items were rated using a 6-point Likert scale assessing teacher's

own perceptions about the importance of intelligence, its malleability, and relation to mathematics capability (1=Strongly Disagree, 6=Strongly Agree). The factor displayed high internal consistency (sample $\omega = .94$).

Teacher self-efficacy. A total of 14 items were available as indicators for a teacher self-efficacy in mathematics instruction latent construct. I conducted principal axis factoring with all items to reduce the number of indicators. Ten items were removed because they negatively impacted internal consistency estimates using Cronbach's alpha. The remaining four-item construct used items based on either a 5-point Likert scale (1=Disagree, 5=Strongly Agree) or 7-point Likert scale (1=Not at all, 7=A great deal) assessing agreement with various self-efficacy statements. The construct demonstrated acceptable internal consistency (sample $\omega = .82$).

Instructional effectiveness. Twelve self-report items capturing teachers' own perceptions of the effectiveness of their instructional practices via daily-use frequency of evidence-based instructional practices. When completing these items teachers were asked to reflect on their practices and lesson plans and each item corresponded to one instructional practice. I reviewed previous literature on effective upper-elementary math instructional practices (Jayanthi, Gersten, & Baker, 2008; Gersten et al., 2009) to identify items that best capture general, effective math instruction. Seven items of the original twelve were substantiated as evidence-based practices and selected as indicators of the Instructional Effectiveness construct. These items all used a 5-point Likert scale assessing how frequently a teacher believed they used that instructional practice in their daily lessons (1=Rarely or never, 5=Always). All together, these items assessed how often a teacher used concrete manipulatives to demonstrate concepts and procedures, judicious

review and question-and-answer sessions with students to test for conceptual knowledge, instruction in and application of multiple strategies to solve problems, formal and direct instructional techniques to introduce topics, routine algorithm practice in class, routine class and home-based practice work, and tested computational and math fact skills in class, particularly during math procedure lessons. These items were summed to create a composite index of teacher's self-reported usage of effective instructional practices (range=0-35).

Teacher background. Several teacher training background variables were selected to use to predict latent teacher classes (procedure described below). Teachers were asked to provide the number of years they had been employed as teachers. They also were asked to report on their training experience, earned a masters education in elementary education, and the types of courses they received in their undergraduate training that directly related to instructing mathematics, including mathematics courses that strengthened teachers' own understanding of math content, courses on appropriate math content for elementary education, and pedagogical courses for elementary mathematics education.

Student engagement. There are a few self-report measures of student engagement with psychometric evidence supporting their reliability and validity. For example, the Student Engagement Instrument (SEI; Appleton, Christenson, Kim, & Reschly, 2006) is an instrument that was developed explicitly to assess aspects of student engagement. The SEI displays strong reliability and construct validity properties; however, it only captures two dimensions of student engagement. Instead of using only one instrument such as the SEI, the NCTE researchers chose to incorporate items from

several separate instruments into their student survey. Despite being based on measures with psychometric evidence, this new student survey lacked psychometric evidence that the items retained their factor structure. Some exploratory analyses were conducted by the NCTE researchers but it was necessary for this study to engage in more analyses. Specifically, it was critical that there was some evidence for items to be used as indicators of the hypothesized constructs before included in the confirmatory factor analysis procedure included as part of structural equation modeling. A brief overview of the student self-report questionnaire is provided below including some of the preliminary exploratory work. I then briefly discuss the exploratory analyses used in this study.

The student engagement measure was constructed from a combination of items selected from *Tripod*® student surveys (“*Tripod*®”, 2018), Measures of Effective Teaching (MET, 2018), and researcher-developed items adapted from National Assessment of Educational Progress (NAEP, 2018) and Trends in Mathematics and Science Study (TIMSS, 2018) surveys. Recent exploratory work determined a few reliable constructs (self-efficacy, happiness in class, behavior in class) emerged each year of the study (Blazar & Kraft, 2017), but some constructs (affective engagement) were less stable across all three waves. This is potentially because the wording of some items, and the total number of items per construct, changed each year. To determine appropriate items per student engagement construct in wave 2, I first reviewed stem content and selected fifteen items. Two preliminary data reduction techniques were used to determine the plausibility of three engagement constructs. The first technique was exploratory factor analysis using maximum likelihood estimation. Items were allowed to cross-load onto multiple factors and several hypothetical factor structures were tested. The second

technique was hierarchical clustering using Pearson r correlation as the measure of distance between items. Visual analysis of a dendrogram was the primary method for determining the number of appropriate factors within this technique. Both techniques corroborated a three-factor structure, although there were differences in which items clustered together under each factor. Three items did not share a common factor across both techniques and were eliminated. Another three demonstrated very low loadings on their respective factors and were eliminated. This left nine items separated into three student engagement constructs. Each of these are described below.

Affective engagement. Affective engagement is a construct representing a student's positive and negative emotional experiences related to school (Appleton, Christenson, & Furlong, 2008). This encompasses their relationship with peers and teachers, perceptions of school climate, and feelings of inclusiveness or belonging. A longstanding history of work has connected affective engagement with school achievement (e.g., Goodenow, 1991), and some work has connected the achievement and opportunity gaps for children historically disadvantaged backgrounds partially to a lack of affective engagement (Voight, Hanson, O'Malley, & Adekanye, 2015). Within this study, student affective engagement was comprised of three items capturing a student's perceived relationship with their teacher and sense of belonging in the classroom (e.g., "If I am sad or angry, my teacher helps me feel better"; McNeely & Falci, 2004). Items were rated on a 5-point Likert scale (1=Totally untrue, 5=Totally true) and together displayed adequate internal consistency (sample $\omega=.73$).

Behavioral engagement. Behavioral engagement refers to the observable participation of a student in classroom activities or classroom organizations and activities

(Appleton, Christenson, & Furlong, 2008). This construct can be captured with direct observational techniques and basic frequency counts of participation. However, previous research has demonstrated that student self-report of behavior provides a unique perspective of classroom behavior but still correlates moderately with teacher report (Finn & Rock, 1997; Skinner & Belmont, 1993). For this study, three self-report items broadly assessing appropriate behavior in the classroom were selected as indicators of behavioral engagement (e.g., “My behavior in this class is good”; sample $\omega = .76$). Items used the same 5-point Likert scale as the affective engagement items.

Cognitive engagement. Cognitive engagement refers to the degree a student perceives their work as relevant to their lives and interests, and how motivated they are to succeed (Reschly, Phol, Appleton, & Christenson, 2017). Researchers have proposed that cognitive engagement is highly correlated with affective engagement and even potentially a mediator for behavioral engagement (Reschly & Christenson, 2006). This mediation relationship was not tested in this study but was purposefully included because of this demonstrated relationship to the other included engagement constructs. For this study, three items assessing the student’s interest in mathematics (e.g., “The things we have done in math this year are interesting”) were used to indicate cognitive engagement within mathematics. Items used the same Likert scale as the others engagement items and displayed adequate internal consistency (sample $\omega = .78$).

Math achievement. Student performance on a low-stakes, standard math achievement test was used to assess student math achievement. This assessment was considered low-stakes because student performance on this exam was not used to evaluate teacher performance; therefore, any confounds that may be present during

administration of a state achievement test (e.g., pressure for students to perform well increasing test anxiety and negatively impacting performance) may have been diminished. Item development and parameterization occurred over a three-year period involving intensive pilot testing, item review and calibration procedures, interviews, and consultation to ensure reliability and validity of the alternative assessment (Hickman, Fu, & Hill, 2012). Multiple forms were constructed from the same item pool, and internal consistency assessed using Cronbach's alpha. On average, internal consistency was .85. To establish construct validity, student performance was regressed on performance on the student's state achievement test in addition to a variety of related outcomes after controlling for prior achievement and school-level clustering effects. The bivariate relationship between achievement tests was acceptable ($r=.69, p<.001$), and was significantly related to student ratings of happiness ($r=.08, p<.001$), and value-added (i.e., growth) scores ($r=.51, p<.001$). The test was scored using item response theory (De Ayala, 2013) and ranged from -3 to 3.

Analysis Plan

Different data analytic procedures were used to address the three main research questions. Analyses were designed to build upon one other. Inferences drawn from one analysis fed into model construction and interpretation of later analyses. When viewed as a whole, each research question and its accompanying analyses are sequenced within a broad study investigating the relationship between teacher-level factors and student engagement and achievement. The analytic sample is reviewed below, followed by a discussion of each analysis in the order they occurred.

Analytic Sample. The analytic sample for the present study included 4th and 5th grade students ($n = 3,550$) and their teachers ($n = 161$) from the second wave of data collection. Data cleaning eliminated duplicate cases and student and teacher cases missing data indicating students' grade. Any other missing data were addressed using maximum likelihood described below.

Research questions 1 & 2. Structural Equation Modeling (SEM) was used as the analytic method for research questions 1 and 2. SEM is a combination of factor analysis and multiple regression techniques. It imposes a measurement model that specifies the relationship between variables now considered observed indicators of a theoretical latent construct and a structural model that specifies the relationship between those constructs. This affords researchers the ability to define direct and indirect relationships between variables; that is, SEM uses the observed relationship between variables to determine plausible causal relations (Maruyama, 1997). An important note is that SEM does not infer causality but merely tests if causal relationships between constructs are plausible. Thus, it is important that SEM primarily be used to confirm complex models, not explore them as many models may fit the same data. Theory must underpin a model.

Another benefit SEM affords researchers beyond plausible causality modeling is the recognition that measurement is difficult and error-prone. This creates a potential cascade of confounding error when determining relationships between constructs. SEM includes multiple indicators of a construct and explicitly models measurement error to generate unbiased estimates (Maruyama, 1997).

On average, 3.1% of data were missing for indicator variables. Full information maximum likelihood (FIML) was used to account for missing data and parameter

estimation (Arbuckle, 1996). FIML computes a likelihood function for each case based on the complete observed data for that case, using the variance and covariance matrix of observed data unique to each case. Parameters are estimated then from the accumulated likelihood functions from the entire sample. Thus, parameters are estimated from cases which provide data for that parameter (e.g., prior achievement in this study) but also allow for the inclusion, instead of deletion, of cases missing data for that parameter due to the observed correlation between that variable (prior achievement) and other variables an incomplete case may have (e.g., student self-efficacy). FIML is highly robust to missing data under the MCAR and MAR conditions and is especially useful in SEM. One SEM simulation study determined that FIML was superior to listwise and pairwise deletion, and imputation, with respect to convergence failures, model fit indices, bias, and estimation efficiency (Enders & Bandalos, 2001).

In addition, FIML also allows for model estimation using raw data instead of sample covariance matrices. As such, multilevel modeling techniques can be merged with SEM to account for clustered (i.e., dependent) data structures (Heck & Thomas, 2015). When using FIML, SEM becomes a quite flexible technique, given adequate sample size, high quality data, and strong foundational theory to guide model testing. For this study, students were clustered in teachers, with between-cluster variables including teacher variables and within-cluster variables including student variables.

Four models were fit, beginning with a base model reflecting past research (Base Model). This model posited that a teacher's self-efficacy and instructional effectiveness were correlated with one another and that both exhibit unique influences on student affective, behavioral, and cognitive engagement. These, in turn, were correlated with

each other and directly influenced student engagement. The Mindset Model kept this same structure and added in Teacher's Implicit Theory of Intelligence as a latent variable correlated with the other teacher variables and exhibiting unique influences on student engagement. The Partial Mediation Model tested a partially mediated model by specifying direct paths between teacher beliefs and instructional effectiveness. The Full Mediation Model was a full mediation model in which the direct paths from teacher beliefs to the engagement latent constructs were constrained to zero so that their effect could only be modeled indirectly through instructional effectiveness.

Model fit was assessed according to a collection of fit indices including generalized likelihood ratio test between models (X^2), Goodness of Fit and Comparative Fit Indices (GFI and CFI, respectively), Tucker Lewis Index (TLI), Standardized Root Mean Square Residual (SRMR), Root Mean Squared Error of Approximation (RMSEA), and Bayesian Information Criterion (BIC). Specifically, we looked for the model that had a nonsignificant chi-square², GFI, CFI, and TLI >0.90, an RMSEA preferably <.05 but at least with the upper band of a 95% confidence interval <.08 (MacCallum, Browne, & Sugawara, 1996), a SRMR <.08 (Hu & Bentler, 1999), and the lowest BIC. These cutoffs were treated as "soft" cutoffs based on interpretative caution expressed by McNeish and Hancock (2018), who found preliminary evidence that measurement error impacts the underlying ontology of these cutoffs such that a model built from poor measures may inflate model fit indices. Considering the lower internal consistencies of some of the constructs in this study, I anticipated some upward bias in the indices. Regarding testing

² This index is highly susceptible to large sample sizes. I anticipated receiving significant results and weighed this index less in my determination of model fit.

nested and mathematically equivalent models (Mindset-Full Mediation), the best fitting model was chosen based on changes in path loadings, model fit indices, likelihood ratio tests, and overall simplicity of the model. Data were prepared in base *R* (R Core Team, 2018) and models fit using MPlus8.1.

Holdout Validation. A common issue facing statistical inference is overfit (Babyak, 2004). Overfit occurs when the complexity of a model as a function of the number of parameters included and degrees of freedom used exceeds the structure of the data. Thus, residual variation is mistakenly extracted and parameterized without a true, ontological basis. Overfit can result in a well-fitting model that fails to predict outcomes, generalize to alternative but related samples, or accurately reflect the underlying theory (Roberts & Pashler, 2000). To address overfit and increase the generalizability of the final structural equation model, I implemented a holdout validation procedure (Refaeilzadeh, Tang, & Liu, 2009) commonly used in machine learning. Hold-out validation involves partitioning a complete dataset into two non-overlapping datasets: a training set and a testing set. Models are developed and modified using the training set. Once a final model(s) is selected, it is fit to the testing set. The primary benefit of hold-out validation is that it directly tests for overfit and builds in replication into a single analysis. However, a common criticism is that it reduces the information in the training set, potentially even eliminating invaluable information for model development, thus introducing bias into the selected model(s). In addition, the structure of the training and testing sets is dependent upon the criteria selected for the data partitioning (Refaeilzadeh, Tang, & Liu, 2009). Acknowledging these criticisms, I decided to randomly partition the sample at the teacher-level into a 60/40 split. The training set contained 2,150 students

and 97 teachers. The testing set contained 1,400 students and 64 teachers.

Because students were nested in teachers, I wanted to ensure that 1) I had enough teachers in both the training and testing sets to avoid bias in hierarchical models (discussed below), and 2) that each teacher contained enough students to avoid biased student-level estimates. According to Maas and Hox (2005), cluster sample-sizes (i.e., the number of teachers in a sample) of 30, 50, and 100 result in unbiased regression coefficient estimates and unbiased individual-level (i.e., students) variance estimates. This remained true regardless of the individual-level sample sizes (i.e., the number of students per teacher), even in cases where the individual-level sample size was quite small ($n=5$). However, the standard errors of the cluster-level variances are underestimated when the number of clusters drops below 100. This results in an increased type 1 error rate (i.e., rejecting the null hypothesis when the null is true). Maas and Hox (2005) note, though, that when cluster-level sample sizes is 50, the inflated error rate is not too egregious and “in practice probably acceptable” (p.91). Both the training and testing sets met this minimum criterion for clusters. Therefore, when considering individual-level sample sizes, I decided to maintain as much of the cluster sample as possible and eliminated only teachers with less than five nested students. This eliminated one teacher with four students from the testing set, leaving a final sample size of 1,399 students and 63 teachers.

Power analysis. Several power analyses were conducted based on the final structural model. Four effect sizes were of primary interest. The first was the path from a teacher’s self-efficacy to their instructional effectiveness. The second was similarly the path from a teacher’s implicit theory to instructional effectiveness. The third effect size

was the average path coefficient from instructional effectiveness to the three separate domains of engagement. The final effect size was the average effect size from the three domains of engagement to the achievement test. Based on prior research, the relationship between instructional effectiveness and self-efficacy was estimated to be moderate from .2-.3. Considering there was less research on the relationship between teacher implicit theory and instructional effectiveness, a range of coefficients from .1-.6 were conducted. The relationship between instructional effectiveness and engagement was estimated to be moderate at .3. Finally, the relationship between engagement and achievement, based on prior research, was considered to be moderate, ranging from .3-.4. Results revealed that, with $\alpha=.05$, these varied combinations of effect sizes would need a sample size ranging from 24 to 90 at the cluster (teacher) level. The training set fell in this range although the testing set did not, potentially limiting the ability to find small and significant effects.

Research question 3. Latent-class analysis was used to determine teacher profiles according to social-cognitive and instructional factors. Latent-class analysis is a derivative of structural equation modeling and is classified as a special case of mixture models. In general, structural equation models focus on the relationship between latent, or unobservable, traits and constructs (e.g., motivation, IQ). Because these traits are unobservable, multiple indicators are used in conjunction with factor analysis techniques to determine if those indicators, do in fact, all measure the same thing. Combined, the relationship between these indicators are used within multivariate regression techniques in attempt to model theoretical causal relationships. LCA replaces the latent trait with a latent class and uses multiple person-level variables from cross-sectional data to determine the number of classes and who belongs to each class. These classes are

homogenous within-class (i.e., individuals are the same within) and heterogeneous between-groups (i.e., classes are independent of one another). In this way, each class is a latent variable and particular indicators load onto each. The patterns of responses on these indicators in an individual determines probability of class membership. Covariates may be included in a binomial or multinomial logistic regression to both improve classification and determine variables significantly related to latent class prevalence (Collins & Lanza, 2010).

Teacher responses to the self-efficacy, implicit theory, and instructional practices items were used in the LCA procedure. Models with two classes through eight classes were analyzed and compared using multiple model fit indicators including Bayesian Information Criteria (BIC) and its reduction from model to model, Bootstrap Likelihood Ratio Test (BLRT), Entropy, and overall interpretation and parsimony (Marsh, Lüdtke, Trautwein, & Morin, 2009; Nylund, Asparouhov, & Muthén, 2007). These fit statistics do not have cutoff scores but combined can be used to guide decision-making regarding the most appropriate model. BIC and BIC reduction are descriptive fit indices. BLRT enables the comparison of an estimated model with k classes to a model with $k-1$ classes. A significant p -value ($< .01$) suggests that the estimated model is a better fit. Finally, larger entropy values (closer to 1) indicate better fit of individuals to their respective classes. To corroborate model fit indices for class enumeration, indicator means were plotted to visually determine how well the teachers separated into distinct classes.

Latent class analysis is an empirically-driven method that is theory-guided. Thus, it is possible to determine profiles that are not reliable, valid, or align with theory. To test for reliability and validity, two related but separate approaches were used. First, class

membership for each individual were regressed on a set of teacher-level background variables using multinomial logistic regression. Since both efficacy, implicit theory, and instructional practices are likely to be informed by training, education, and cultural factors, these were hypothesized to adequately predict class membership. Multinomial logistic regression relies upon several assumptions. The most critical assumption is absence of multicollinearity in predictor variables. Bivariate correlations and the variance inflation factor (VIF) were used to assess multicollinearity. VIF values above 10 indicated multicollinearity and those items removed from the predictor model. Model fit was assessed using Cox and Snell, Nagelkerke, and McFadden pseudo R-Square values.

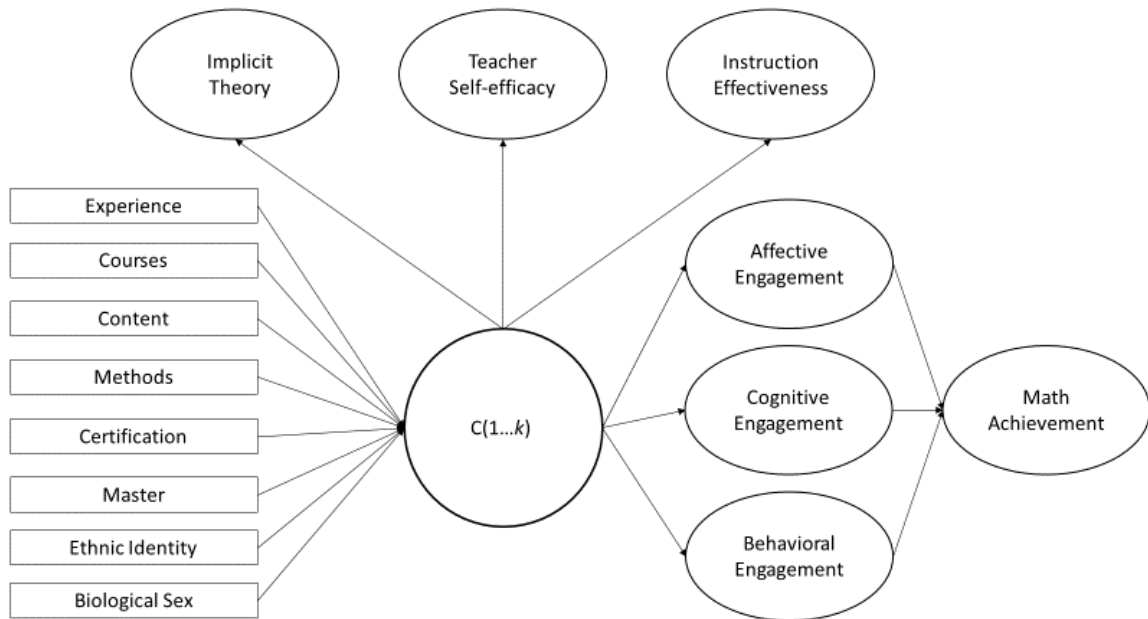


Figure 5. An illustration of the overarching analytic procedures used in this study. Starting with the middle circle, this symbol represents the hypothesized teacher profiles to be uncovered using LCA. It is hypothesized that there is 1 to k number of classes. These classes are predicted by the individual and training factors that are listed on the left of the diagram. These teacher classes, in theory, contribute to the disparate measures of teacher self-efficacy, implicit theory, and their instructional effectiveness.

Simultaneously, these underlying classes also predict student engagement and math achievement.

Predicting class membership using multinomial logistic regression a common method for identifying, predicting, and then using empirically derived latent classes for further analyses (Collins & Lanza, 2010; Petersen, Bandeen-Roche, Budtz-Jørgensen, & Larsen, 2012).

The second method determined the classes predictive validity. Multivariate bivariate regression analyses with class membership included as factor variable and a random effect was used to assess teacher class differences on student engagement and math achievement.

Chapter 4: Results

Descriptive and correlational results are discussed first, followed by a review of the results of the structural models using the training set, including how the models were adjusted to provide better fit to the data. Next, the model validation process using the test set is reviewed. Last, the results from the latent class analyses are discussed, including model fit, logistic regression, and the final multivariate regression analysis including the derived latent classes.

Descriptive Statistics

Table 2 presents means and proportions of various demographic and background variables for the training and test set, with a total percent missing across both datasets. Overall, the two datasets were equivalent regarding their student samples. A small majority of students were male (51.2%) and identified with a Black American racial background (42.7%). More than 50% of the participants from the two samples were enrolled in a free and reduced lunch program, which is above the national average (McFarland et al., 2017). The number of students receiving special education services was below the national average of 13% (McFarland et al., 2017), and the proportion of those considered English Language Learners was greater than national average of 9.4% (McFarland et al., 2017).

Regarding teachers, differences were observed between the two samples. Most teachers were female (91.3%) and identified as coming from an African American (42.6%) or White racial (40.2%) background. These were equivalent across the two datasets. However, variability across the two datasets were noted among teachers'

training history. In general, teachers in the test set appeared to have greater training in mathematics, while less training in elementary mathematics content and instructional methods. A larger percentage of teachers in the test set had earned a master's degree in education compared to their peers in the training set, and, on average, had more years of experience (not statistically significant). The degree to which these differences are attributable to missing data was unknown as most teachers did not report these data. I conducted simple logistic regression to explore potential underlying missing data mechanisms by creating dummy variables for each teacher variable indicating missingness status. I then regressed missingness on a few select variables including school site and grade. No variable was statistically significantly related to missingness, suggesting that missingness may be unsystematic or systematically related to some confounding factor not captured by the available data.

Table 2

Demographic statistics as means and proportions

Variable	Training Set	Test Set	% Missing (Total Sample)
Student (<i>n</i>)	2,150	1,400	--
<i>Demographics</i>			
Grade			1.3
4 th	50.5	50.9	
5 th	49.5	49.1	
Biological Sex (male)	50.2	52.2	0
Race/Ethnicity			0

African American	42.0	43.4	
Pacific Asian	6.3	7.0	
Hispanic	17.7	17.5	
White	29.1	29.0	
Other	4.9	3.1	
Free-reduced Lunch	58.7	58.5	0
Special Education Status	11.5	10.7	0
English Language Learner Status	14.7	14.9	0
Teacher (n)	97	64	
<i>Demographics</i>			
Biological Sex (male)	11.1	6.3	77
Race			76
African American	38.1	47.1	
White	33.3	47.1	
Multiracial	4.8	0	
Other	4.8	0	
<i>Training Background</i>			
Years Experience <i>M (SD)</i>	12 (9.5)	14.2 (7.7)	75
Math Courses			76
No Classes	0	5.9	

One or Two Classes	19.0	29.4	
Three-to-five Classes	61.9	41.2	
Six+ Classes	19.0	23.5	
Math Content			76
No Classes	19.0	11.8	
One or Two Classes	28.6	41.2	
Three-to-five Classes	38.1	29.4	
Six+ Classes	14.3	17.6	
Math Methods			76
No Classes	19.0	23.5	
One or Two Classes	33.3	35.3	
Three-to-five Classes	38.1	29.4	
Six+ Classes	9.5	11.8	
Certification			76
Teacher Ed Program	68.4	87.5	
Alt. Certification	10.5	6.3	
No Formal Training	21.1	6.3	
Master's Degree	61.9	76.5	76

Table 3 presents zero-order correlations and descriptive statistics for all outcome and indicator variables. Correlations between indicators of the same latent variable were

generally moderate-to-high, ranging from .18 to .88. The largest correlations were between indicators of teacher variables; specifically, the four indicators for a teacher's implicit theory of their students' intelligence demonstrated the largest relationships. The stems of these items were all similarly worded, more so than compared to indicators of other variables. A portion of these strong correlations may have resulted from shared method variance. Correlations between indicators of dimensions of student engagement varied in magnitude and were all positively related. In general, students reported similar levels of engagement across all dimensions, such that a behaviorally engaged student was more likely to be engaged affectively as well. However, these items were not perfectly correlated, lending continued support to the idea that affective, behavioral, and cognitive engagement are related but distinct subfactors of a broad student engagement construct.

Self-reported ratings of behavioral engagement demonstrated the largest and most consistent relationship with performance on the math test. Only one affective and one cognitive engagement variable—AE3 and CE3—were related to math performance. Their correlations were notably small and in opposite directions.

At the teacher level, indicators varied in the magnitude of correlations. A consistent pattern between indicators of teacher's implicit theories and their self-efficacy and instructional practices emerged. While the sum index of instructional practices and measures of teacher self-efficacy were positively correlated, they all correlated negatively with implicit theory, such that the more a teacher endorsed an incremental theory, i.e., a growth mindset about student intelligence, the lower they rated their self-efficacy and they reported using fewer effective instructional practices.

Relationships between teacher variables and student variables were notably smaller and varied in their statistical significance. Math performance was related to most teacher indicators with the largest correlations of .11 and .10 for TSE4 and TIT2, respectively. This was reasonable though as these teacher indicators were distal to math performance and, as was later tested within

Table 3

Zero-order correlations, means, and standard deviations of all indicator and outcome variables

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	M	SD
1. TEST	-	.18**	.26**	.24**	.04	0	-0.4*	.02	.03	.08**	-	0	.08**	.05*	.11**	.08**	.10**	.05*	.03	.49	1.11
2. BE1		--	.51**	.50**	.20**	.16**	.19**	.19**	.21**	.22**	-.04	.04	.05*	.05*	.06**	.05*	.07**	.04	.01	4.28	0.89
3. BE2			--	.57**	.18**	.12**	.13**	.08**	.10**	.14**	-.04	.04	.07**	.07**	.09**	.05*	.06**	.05*	.02	2.16	1.36
4. BE3				--	.18**	.11**	.16**	.08**	.12**	.13**	.04	.02	.06**	.03	.06**	.06**	.08**	.06**	.04	1.67	1.10
5. AE1					--	.48**	.51**	.32**	.46**	.43**	-.02	.03	.07**	.03	.07**	-.01	-.02	-.02	-.01	4.40	0.96
6. AE2						--	.39**	.29**	.40**	.34**	0	.04	.05*	.02	.04*	-.01	-.02	-.02	-.02	4.61	0.80
7. AE3							--	.33**	.45**	.43**	0	.03	.06**	.05*	.06**	-.05*	-	-.03	-.02	3.72	1.38
																	.06**				

TEACHER BELIEFS AND BEHAVIORS IMPACT ENGAGEMENT

8. CE1	--	.46**	.48**	0	-.03	0	0	.03	-.02	-.01	-.03	-.02	4.06	0.99
9. CE2	--	.65**	.01	0	.02	0	.03	-.02	0	-.02	-.01	4.05	1.19	
10. CE3	--		0	.01	.03	-.01	.05*	-.03	-.01	-.03	-.02	4.17	1.11	
11. IESum	--			.18**	.15**	.19**	.10**	.13**	.12**	-.05*	-.05*	26.7	5.29	
12. TSE1	--				.60**	.49**	.45**	.28**	.29**	.24**	.14**	5.40	1.15	
13. TSE2	--					.53**	.38**	.27**	.26**	.26**	.17**	5.63	1.15	
14. TSE3	--						.59**	.16**	.19**	.20**	.18**	5.92	1.04	
15. TSE4	--							.15**	.16**	.13**	.10**	6.11	0.93	

16. TIT1	--	.88**	.82**	.75**	2.33	1.04
17. TIT2	--		.81**	.75**	2.31	0.99
18. TIT3			--	.78**	2.60	1.19
19. TIT4				--	2.30	1.03

Note. * $p < .01$, ** $p < .001$.

Correlations are zero-order correlations using Pearson's r . Based on Davison and Sharma (1994), all Likert items were treated as continuous.

structural models, likely only acted their influence through student engagement. Surprisingly, the instructional effectiveness summative index—arguably the most proximal of all the teacher variables—demonstrated a small and negative correlation with performance.

These correlations helped inform the structural equation modeling analyses. Instructional effectiveness would likely not result in any significant paths as the zero-order correlations indicated mostly null relationships between instruction and engagement, although some relationship was observed for math performance. Since this was a key theoretical variable, no model modifications were implemented with this variable. Correlations between affective, behavioral, and cognitive engagement warranted modeling these variables under a higher-order engagement factor in alignment with theory. However, this would complicate the model, potentially introducing convergence issues, and could mask the unique influence of each engagement factor on math achievement. I decided to keep the factor separate and model correlations between them.

Interclass correlations (ICCs), nesting students within teachers, were calculated for all student-level indicators and math performance. ICCs for the affective engagement indicators (AE1-3) were .07, .13, and .13, respectively. ICCs for the behavioral engagement indicators (BE1-3) were .07, .08, and .1, respectively. ICCs for the cognitive engagement indicators (CE1-3) were .19, .09, and .15, respectively. The ICC for math performance was 0. Collectively, these ICCs suggesting notable nesting of student outcomes within teacher and supported the necessity of using multi-level SEM.

Below are the results from the structural equation models. For each model, the results from the training set and any model modifications based on empirical and

theoretical reasons are discussed. Then, a more detailed explanation of model outcomes after fitting the adjusted model to the test set is described.

Teacher Self-efficacy and Instructional Model (Base Model)

The Base Model included teacher self-efficacy and instructional effectiveness as predictors of student engagement, with direct paths connecting these teacher variables to all three engagement factors. This model mimicked past research comparing these variables and was intended as a replication. Initial fit of the model to the training set resulted in mixed findings across the fit indices. Some, such as RMSEA, were within acceptable levels ($<.07$) but others—specifically, TLI and CFI—were not. In addition, although the model fit, the best likelihood was not replicated, despite manipulating starting values. Review of modification indices suggested correlating the residuals of the teacher self-efficacy indicators (TSE1 with TSE2 and TSE3; TSE4 with TSE2 and TSE3). This suggested that the second and third indicators were particularly relevant to this latent variable. A review of the stems determined that all indicators captured broadly the construct of self-efficacy yet the first three measured a motivational efficacy, whereas the fourth measured behavioral self-efficacy. Covarying the residual of the first residual improved all fit indices and the best likelihood for the model was able to be replicated even after manipulating starting values in MPlus. In addition, model fit indices determined that fixing the variances of second cognitive engagement indicator at the student level and teacher level, and the variance of the second behavioral engagement indicator resulted in improved model fit.

This modified Base Model was fit to the test set. Figure 6 displays the model and standardized path loadings (residuals are absent for visual clarity). This model

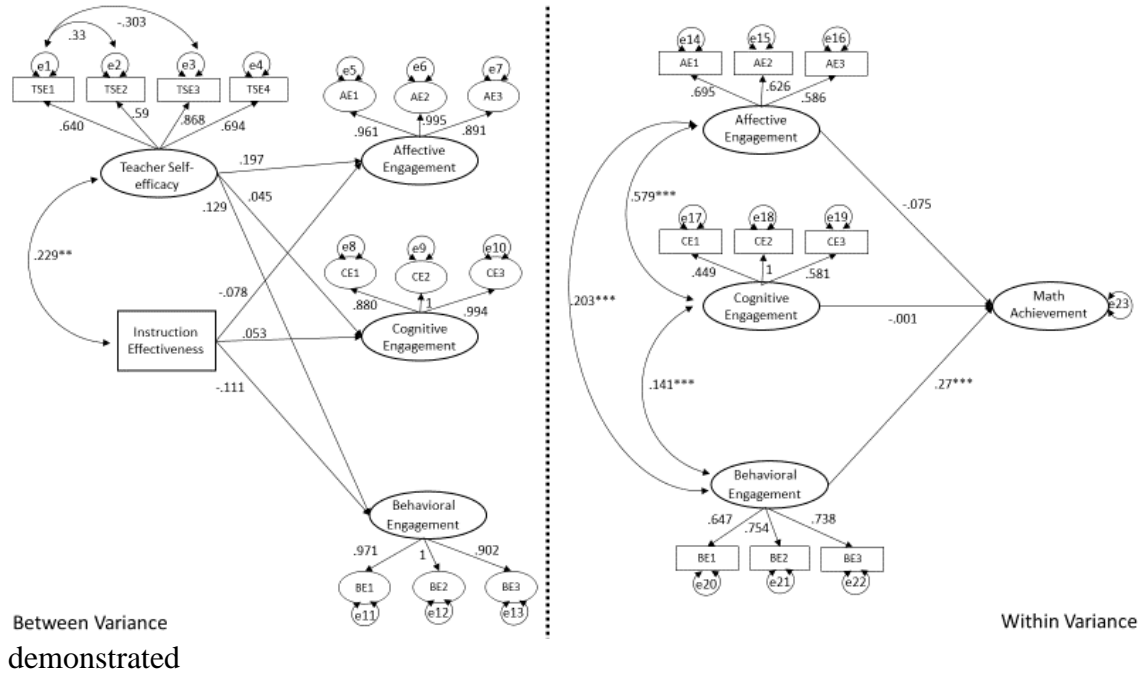


Figure 6. Teacher self-efficacy and instruction model results based on the test set

adequate and desirable fit statistics across all indices. The χ^2 test, with 99 degrees of freedom, was significant at the .001 level; however, as mentioned earlier, this index is easily influenced by sample and was weighted less in determining overall model fit adequacy because of this study’s sample size. The BIC value was 38,096. CFI, TLI, and RMSEA were .92, .89, and .05, respectively. SMR at the within and between levels was .05 and .11, respectively. At the student level, affective, behavioral, and cognitive engagement explained 7% of variance in math performance. At the teacher level, teacher self-efficacy and instruction explained 5, 3, and 1% of variance in affective, behavioral, and cognitive engagement, respectively.

At the student level, all behavioral engagement indicators loaded strongly and positively on to the latent variable. Similar results were found for affective engagement indicators. However, loadings were low for cognitive engagement indicators. All three latent variables were significantly positively correlated with cognitive and affective engagement demonstrating the strongest relationship. Behavioral engagement was the only latent variable significantly related to math performance at .27, which can be considered an effect size approaching moderate magnitude.

Factor loadings for all three engagement and teacher self-efficacy latent variables were considerably higher at the teacher-level. Neither self-efficacy or instructional effectiveness were significantly related to any of the student engagement latent variables. However, self-efficacy and instructional effectiveness were moderately positively correlated, indicating that teachers who reported higher efficacy were also associated with greater frequency of using evidence-based practices during their math instruction.

Teacher Self-efficacy, Instruction, and Implicit Theory Model (Mindset Model)

Considering the measurement model at the student level and for the teacher self-efficacy variable remained theoretically unchanged from the Base Model, its model modifications to improve fit were retained. Initial fit of this model to the training set resulted in improved fit without needing further modification. Thus, analyses proceeded by examining model fit with the test set data.

Figure 7 presents the model results based on the test set. Overall, the model demonstrated desirable fit statistics. The χ^2 test, with 152 degrees of freedom, was significant at the .001 level. The BIC value was 40,453. CFI, TLI, and RMSEA were .93,

.91, and .04, respectively. All three of these are a slight improvement over the previous model³. SMR at the within and between levels was .07 and .1, respectively. Since the student level did not change, this model did not improve variance explained in math performance. At the teacher level, teacher self-efficacy and instruction explained 4, 16, and 1% of variance in affective, behavioral, and cognitive engagement, respectively. This was a slight reduction in variance explained in affective engagement but a notable improvement in percent variance explained in behavioral engagement. Factor loadings for teacher self-efficacy indicators adjusted slightly yet self-efficacy and instructional effectiveness remained unrelated to student engagement. The inclusion

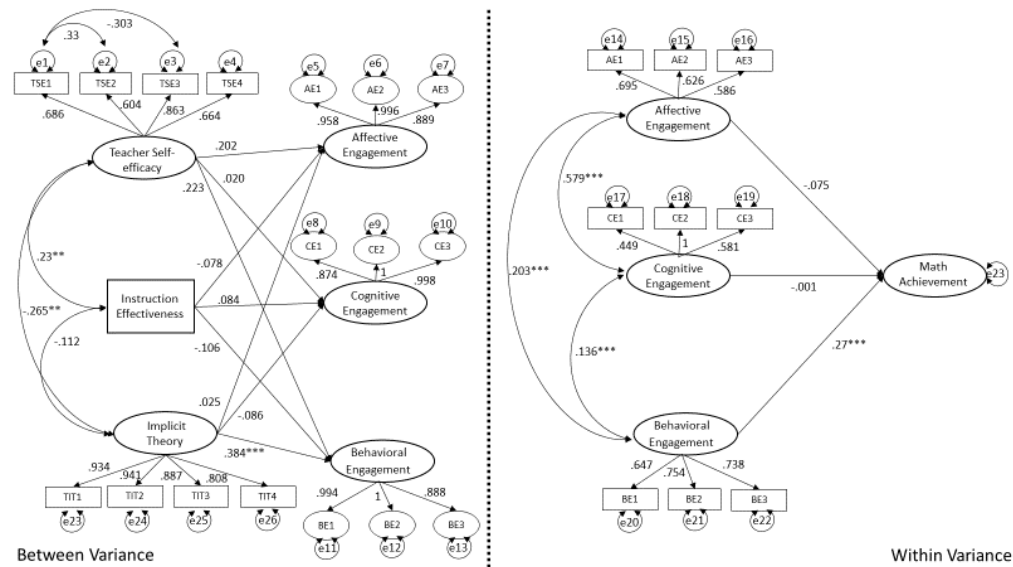


Figure 7. Teacher self-efficacy, instruction, and implicit theory model results based on the test set.

of implicit theory did result in one moderately strong, significant positive effect on behavioral engagement. Teachers that endorsed an overall belief in their students'

³ Since these models involve differences in the number of indicators and latent variables, direct comparisons between models 1 and 2 are only descriptive and not grounded in inferential techniques or based on interpretative guidelines.

capacity to grow their intelligence were associated with greater student behavioral engagement. Since teacher beliefs cannot directly influence student beliefs and behaviors, the follow-up models tested both partial and full mediation of teachers' implicit theory through instructional effectiveness.

Interestingly, examination of the estimate of the relationship between implicit theory and teacher self-efficacy indicated a negative association, suggesting that the more efficacious teachers reported lower belief in the ability for their students to develop intelligence in math.

Partial Mediation Model

Correlations between teachers' implicit theory and self-efficacy, and their instruction were modeled as direct paths with paths between teacher beliefs and student engagement allowed to still vary. The rest of the model remained the same. Model fit indices were acceptable for the training set without need for modification and a replicated likelihood reached so the model was fit to the test set with no changes. Since the previous model and this partial mediation model were mathematically equivalent, descriptive changes in path coefficients between teacher beliefs and student engagement were the primary method for model comparisons.

Figure 8 presents this model. Minuscule and nonsignificant changes were noted in the path coefficients between teachers' implicit theory and student engagement, suggesting that implicit theory was still positively related to student engagement but perhaps through other mediators unmodeled. No changes were observed between teacher self-efficacy and student engagement. Small nonsignificant changes were observed

between instructional effectiveness and student engagement. The paths to affective and behavioral engagement strengthened while the path to cognitive engagement weakened. Finally, fixing the correlation between self-efficacy and instructional effectiveness resulted in a small, significant coefficient (.22) which closely matched the original correlation. Overall, there were few substantial changes in model outcomes, and the full model in which the correlations between beliefs and instructional effectiveness were freely estimated was considered the more parsimonious model. The full mediation model, in which the direct paths from beliefs to student engagement were fixed to 0, was not identified in either the training or test set and therefore not reported.

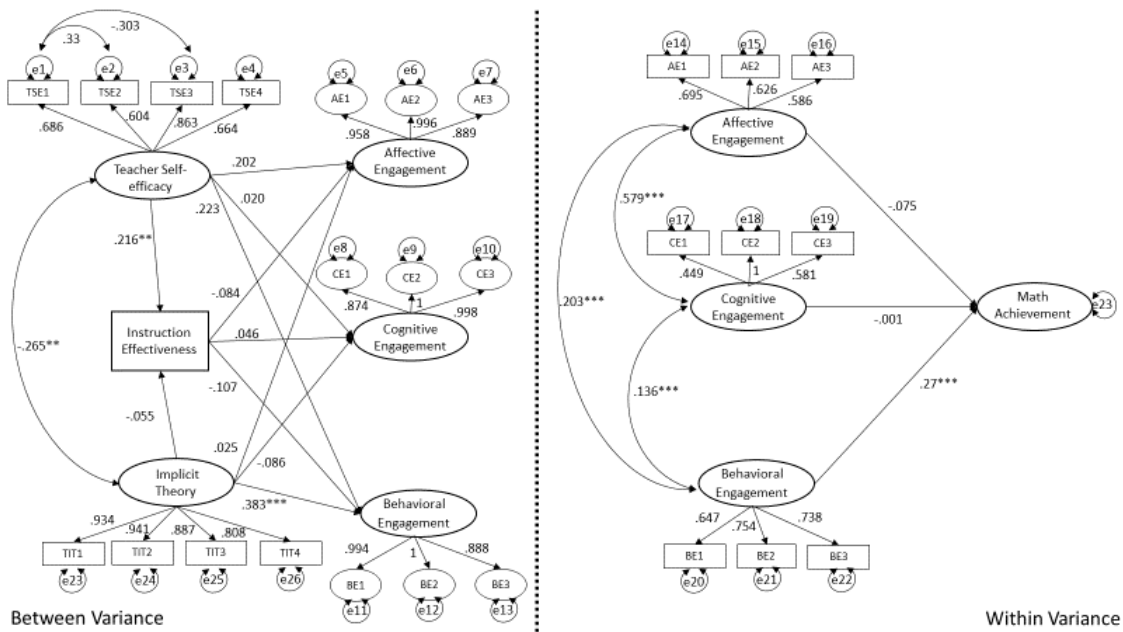


Figure 8. Partial mediation of beliefs through instruction effectiveness.

Latent Class Analysis

After conducting the variable-centered models exploring the relationships between variables, I proceeded with latent class analysis to identify teacher subgroups

that differed in their instructional and social-cognitive factors. Table 4 presents the fit indices for the 2-8 class mixture models.

Table 4

Fit statistics and convergence error problems for 2-8 Teacher Class (TC) models

Statistics	Two TCs	Three TCs	Four TCs	Five TCs	Six TCs	Seven TCs	Eight TCs
BIC	4404.41	4311.98	4276.77	4259.38	3978.46	3910.45	4235.06
	1	5	8	9	2	1	0
% BIC Reduction	--	2.1	.82	.41	6.6	1.71	-8.30
Entropy	.953	.938	.939	.941	.978	.985	.932
BLRT	--	0	0	0	0	1	1
# of convergence errors	0	0	0	0	1	2	2

Note. The seven- and eight-class models did not converge with a replicated likelihood. In addition, the six- thru eight-class models reported issues with certain indicators having no variability within one or more classes and thus causing potential issues with fit and estimates.

The 6,7, and 8-class models were eliminated due to failure to replicate likelihood values and low variability for implicit theory items for certain classes resulting in errors. Based on model fit indices, the 2-5 class models were likely candidates. No single model demonstrated the best fit across all indices. Entropy, a measure of the distinction between classes, favored the two- and five-class models. The reduction in BIC favored the three-class model. All models reported significant bootstrap tests indicating that they all were better fits than a model with one less class. Plots of means of each indicator within classes were plotted for each model to help with class enumeration and model selection

(see Figures 9-12). Visible separation of classes was not noticeable until the four-class model which most closely aligned with the hypothesis of this study. However, the structure of the classes was different than expected. It was hypothesized that classes would mostly differ in the distance between their beliefs and instructional effectiveness; that is, two classes would be considered congruent (beliefs and instruction align) and two classes would be incongruent (beliefs and practices do not align). Instead, the classes appeared to differ primarily in self-efficacy and implicit theory. This distinction was enough to support conceptualizing them as disparate groups instead of different magnitudes of the same overarching class (e.g., low, medium, and high teachers) that the other models indicated.

Overall, all teacher classes in the chosen 4-class model were characterized by objectively high self-efficacy but there were relative differences between them. Similarly, all classes were characterized with high instructional effectiveness. Implicit theory showed the largest variability and was the primary variable differentiating the classes, with subtle differences in self-efficacy further enumerating the classes. Class 1 was labeled “Consistently Low” as their means were generally low across all indicators, especially for implicit theory. Class 2 was labeled “Controversial” as they were highly efficacious and were the most instructionally effective yet reported the lowest implicit theory belief despite the increasing popularity of the growth mindset concept within modern classrooms. Class 3 was labeled “Efficacious” as they reported the highest self-efficacy whereas their other ratings were relatively average. Class 4 was labeled “Believers” as they reported the highest implicit theory belief in students. As far as group membership: 12 (8%) were in the Consistently Low class, 33 (21%) were in the

Controversial class, 58 (36%) were in the Efficacious class, and 56 (35%) were in the Believers class. Table 5 presents average latent class probabilities for the most likely class by final class membership.

Table 5

Average latent class probabilities for the most likely class membership (on rows) based on what class teachers were ultimately assigned (on columns)

	Consistently Low	Controversial	Efficacious	Believer
Consistently Low	.963	0	.035	.001
Controversial	.001	.994	.005	0
Efficacious	.007	.015	.950	.028
Believer	.001	.001	.024	.975

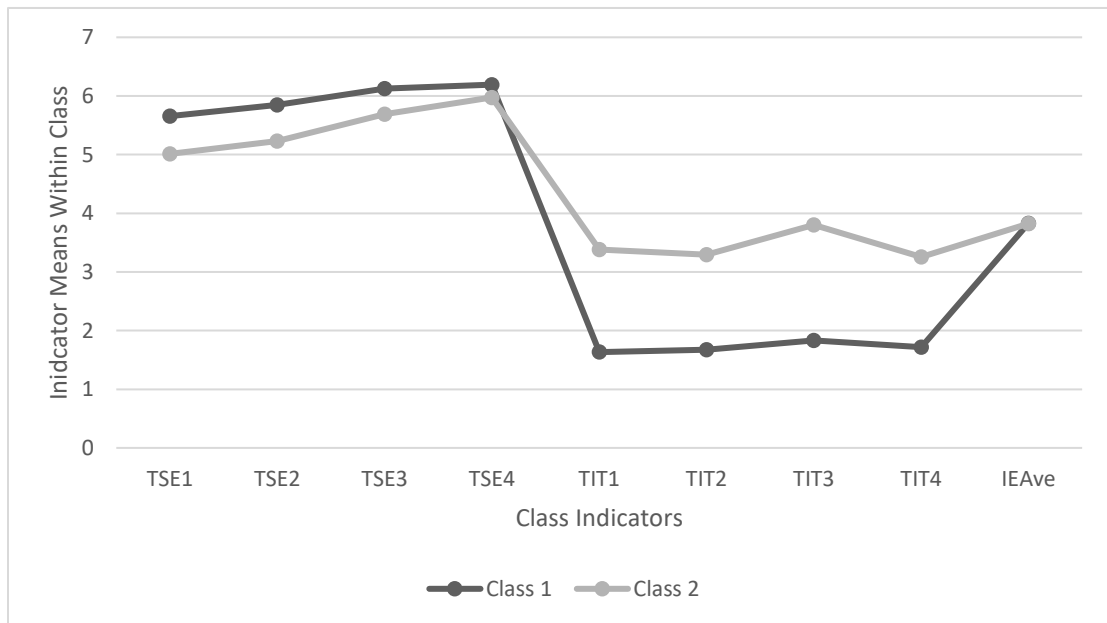


Figure 9. 2-class mixture model profiles using means of each indicator within class. The original instructional effectiveness index variable was divided by 7 (the number of items in the index) to put it on a similar scale (1-5) as the self-efficacy and implicit theory indicators (1-7). Class 1 appeared to be a high efficacy, low implicit theory class. Class 2 appeared to be a less-high efficacy, moderate implicit theory class. Both were high in their instructional effectiveness.

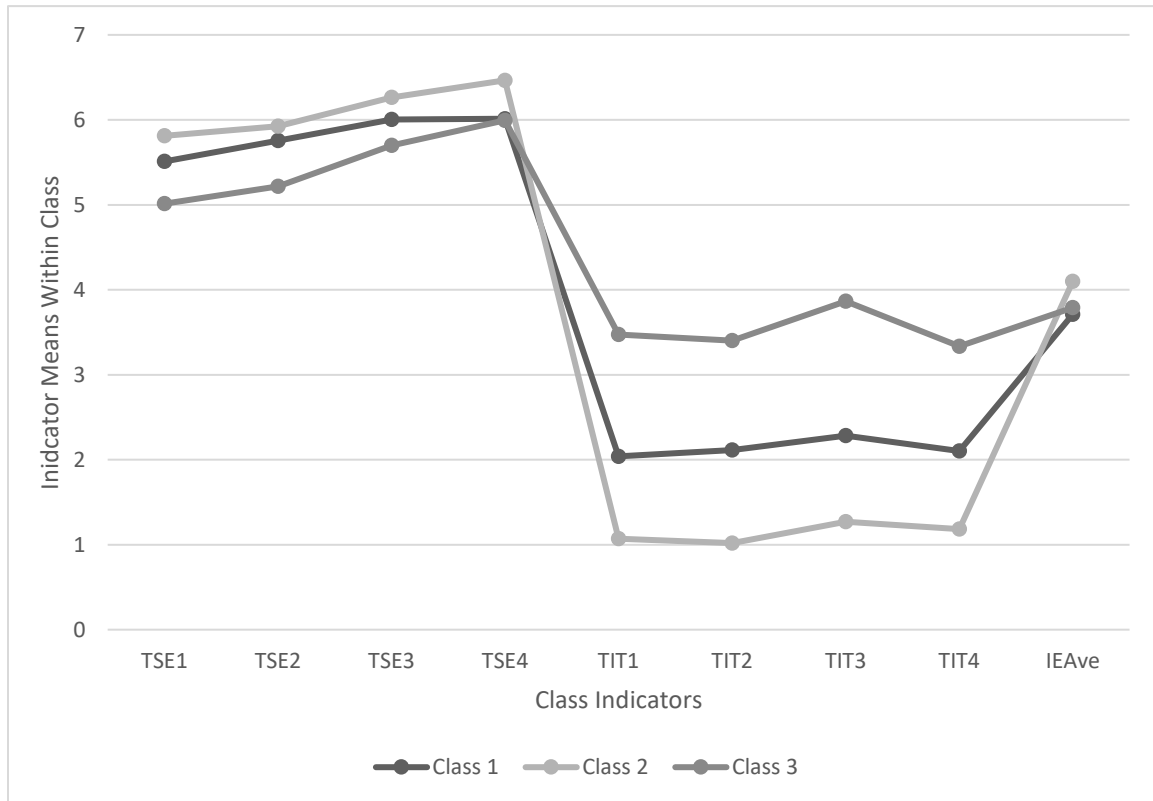


Figure 10. 3-class mixture model profiles using the means of each indicator within class. More separation in the implicit theory indicators is apparent compared to the 2-class model. However, the classes appear to be mostly low, medium and implicit theory versions of a same global class.

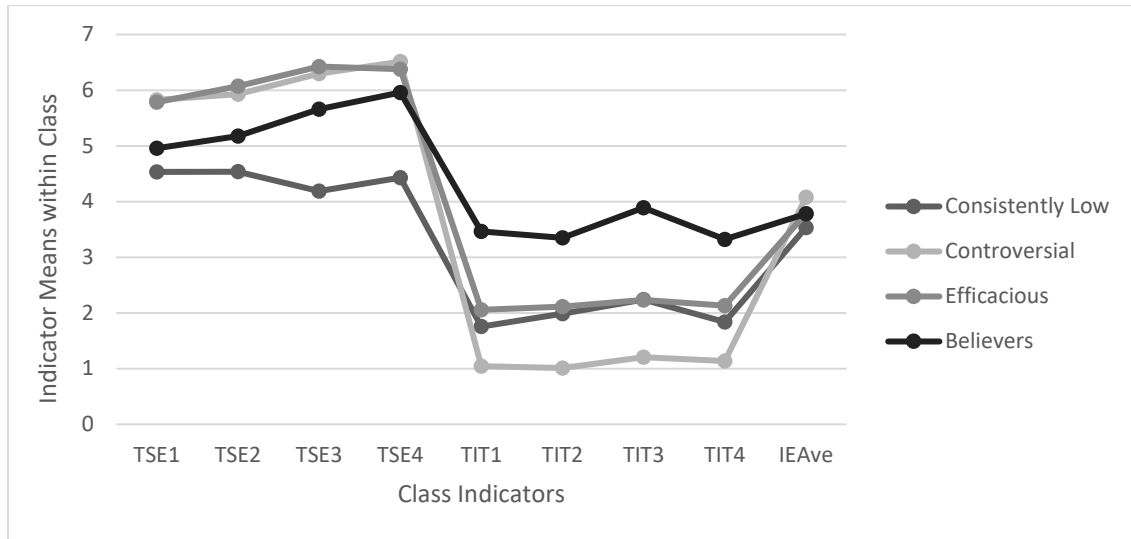


Figure 11. 4-class mixture model using the means of each indicator within class. Since this model was ultimately selected, the classes are labeled in this figure. The same pattern of low, medium, and high implicit theory observed in the 3-class model is still apparent. Yet, there is also greater variation in the trending relationship between self-efficacy and implicit theory that allow for more nuanced interpretation (e.g., elevated self-efficacy does not always relate to depressed implicit theory averages).

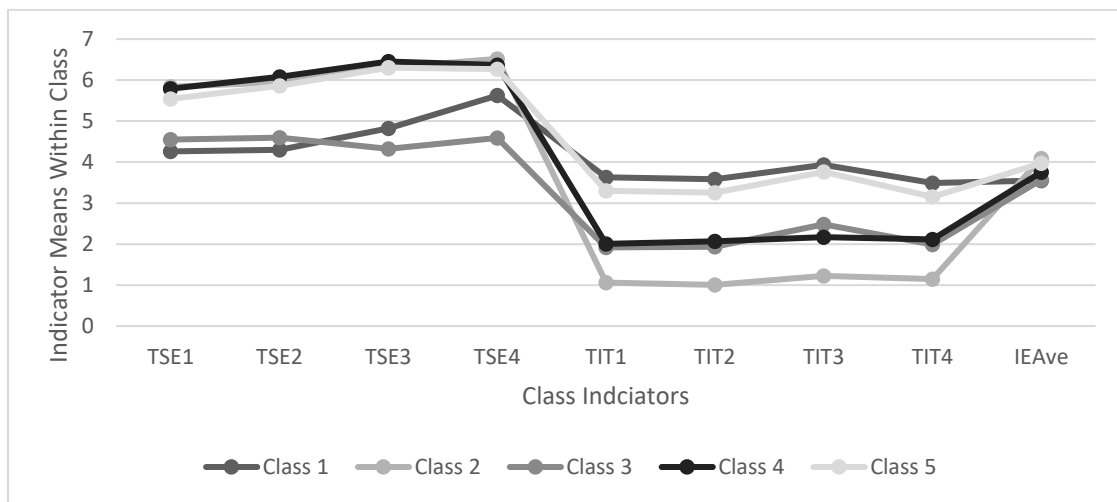


Figure 12. 5-class mixture model using the means of each indicator within class. Although fit indices determined five classes could be enumerated with adequate fit, the actual distinction between classes is less clear. This figure resembled the 3-class model figure (Figure 10), simply with more classes that are not fully distinct. For example, it is difficult to determine how distinct class 1 and 5 are in this figure as their values are nearly identical.

Teacher Latent Class Analysis Regression

Two analyses proceeded the latent class models to determine the validity of the classes. The first analysis was for predicting the classes based on hypothesized related variables. The second analysis assessed the classes predictive validity by testing their association with behavioral engagement and math outcome (the two student outcomes with significant relationships in the structural models).

Predicting teacher classes. Multinomial logistic regressions were conducted first to predict class membership for the entire sample. Models were built in three blocks, beginning first with a model including only training variables, then a second model with racial and ethnic variables, and finally biological binary sex in the third block. The Consistently Low class was used as the referent outcome group. Model fit measures are presented in Table 6 and model estimates in Table 7.

Table 6

Model fit statistics for logistic regression models predicting TC membership

Model	Deviance	AIC	BIC	R^2_{McFadden}	R^2_{Cox}	$R^2_{\text{Nagelkerke}}$	Model Tests		
							χ^2	Df*	p-value
1	1260	1332	1498	.30	.16	.36	528	33	<.001
2	253	349	570	.86	.41	.89	1535	45	<.001
3	116	218	453	.94	.43	.95	1672	48	<.001

Note. Current methods still lack a definite method for determining degrees of freedom within nested data. Degrees of freedom were calculated using the Satterthwaite approximation method (Keselman, Algina, Kowalchuk, & Wolfinger, 1999).

In model 1, years of experience, the number of math courses, and number of math content courses all significantly predicted class membership in all classes compared to the Consistently Low class, except for experience predicting the Believers class (OR=1.05, $p=.28$). Experienced teachers were more likely to be in the Controversial or Efficacious group than the Consistently Low group. The pattern for the number of math courses taken was less consistent. Teachers that took any number of classes were more likely to be in the Controversial Class than those that took zero courses, and those that took one or two classes were 18x more likely to be in the Believers class than those that took zero courses. However, taking three or more classes was more associated with membership in the Efficacious and Believer's group. Teachers that took one or more math content for education courses were consistently more likely to be in the Believers group and consistently less likely to be in the Controversial and Efficacious groups. Pursuing six or more courses in mathematics education methods was consistently linked with a lower likelihood of being in the Controversial, Efficacious, and Believers group. Obtaining a master's degree was associated with a lesser likelihood to be in the Controversial class (OR=0.54, $p=.03$) and marginally associated with a lesser likelihood to be in the Efficacious class (OR=.5, $p=.05$). Overall, these training variables explained approximately 27% of variance averaged across McFadden's, Cox and Snell's, and Nagelkerke's pseudo- R^2 metrics (Allison, 2014).

Table 7

Predicting class membership using a teacher's experience (in years) and related training variables (model 3)

Class Comparison	Predictor	Estimate	SE	Odds Ratio	95% CI	p-value
Controversial-Consistently Low	Intercept	17.19	0.32	2.92e ⁷	1.55e ⁵ -5.52e ⁷	<.001
	Experience	-0.02	0.01	.084	0.81-0.87	<.001
	Math Courses					
	1 or 2 Classes	18.67	0.22	1.29e ⁸	8.32e ⁷ -2.00e ⁸	<.001
	3-to-5 Classes	19.02	0.22	1.82e ⁸	1.18e ⁸ -2.81e ⁸	<.001
	6+ Classes	18.66	0.26	1.28e ⁸	7.66e ⁷ -2.12e ⁸	<.001
	Math Content					
	1 or 2 Classes	-33.70	0.27	2.30e ⁻¹⁵	1.36e ⁻¹⁵ -3.90e ⁻¹⁵	<.001
	3-to-5 Classes	-32.98	0.44	4.76e ⁻¹⁵	2.01e ⁻¹⁵ -1.13e ⁻¹⁴	<.001
	6+ Classes	-11.19	0.32	1.39e ⁻⁵	7.45e ⁻⁶ -2.58e ⁻⁵	<.001
	Math Methods					
	1 or 2 Classes	-0.26	0.38	0.79	0.37-1.62	.491
	3-to-5 Classes	0.02	0.66	1.02	.28-3.69	.979
	6+ Classes	-19.71	0.32	2.77e ⁻⁹	1.49e ⁻⁹ -5.15e ⁻⁹	<.001
	Master's Degree	-125.39	0.15	3.49e ⁻⁵⁵	2.61e ⁻⁵⁵ -4.66e ⁻⁵⁵	<.001
	Hispanic	-615.44	0	5.22e ⁻²⁶⁸	5.22e ⁻²⁶⁸ -5.22e ⁻²⁶⁸	<.001
	Black	-226.97	0	2.67e ⁻⁹⁹	2.67e ⁻⁹⁹ -2.67e ⁻⁹⁹	<.001
White	-40.45	0.15	2.70e ⁻¹⁸	2.02e ⁻¹⁸ -3.61e ⁻¹⁸	<.001	
Multiracial	-116.04	0	4.02e ⁻⁵¹	4.02e ⁻⁵¹ -4.02e ⁻⁵¹	<.001	
Biological sex (Male)	-139.44	0	2.77e ⁻⁶¹	2.77e ⁻⁶¹ -2.77e ⁻⁶¹	<.001	
Class Comparison	Predictor	Estimate	SE	Odds Ratio	95% CI	p-value
Efficacious-Consistently Low	Intercept	104.40	0	2.18e ⁴⁵	2.18e ⁴⁵ -2.18e ⁴⁵	<.001
	Experience	-0.12	0.02	0.88	0.85-0.92	<.001

Class Comparison	Predictor	Estimate	SE	Odds Ratio	95% CI	p-value
	Math Courses					
	1 or 2 Classes	-26.70	0.22	2.56e ⁻¹²	1.66e ⁻¹² -3.94e ⁻¹²	<.001
	3-to-5 Classes	-27.29	0.24	1.41e ⁻¹²	8.74e ⁻¹³ -2.26e ⁻¹²	<.001
	6+ Classes	-26.32	0.26	3.70e ⁻¹²	2.22e ⁻¹² -6.16e ⁻¹²	<.001
	Math Content					
	1 or 2 Classes	-32.91	0.29	5.10e ⁻¹⁵	2.90e ⁻¹⁵ -8.98e ⁻¹⁵	<.001
	3-to-5 Classes	-32.52	0.52	7.53e ⁻¹⁵	2.74e ⁻¹⁵ -2.07e ⁻¹⁴	<.001
	6+ Classes	-21.02	0	3.37e ⁻¹⁴	3.37e ⁻¹⁴ -3.37e ⁻¹⁴	<.001
	Math Methods					
	1 or 2 Classes	0.31	0.41	1.35	0.61-3.01	.457
	3-to-5 Classes	0.19	0.74	1.21	0.28-5.12	.8
	6+ Classes	-28.13	0	3.37e ⁻¹⁴	3.37e ⁻¹⁴ -3.37e ⁻¹⁴	<.001
	Master's Degree	-337.01	0	4.36e ⁻¹⁴⁷	4.36e ⁻¹⁴⁷ -4.36e ⁻¹⁴⁷	<.001
	Hispanic	385.66	0	3.10e ¹⁶⁷	3.10e ¹⁶⁷ -3.10e ¹⁶⁷	<.001
	Black	-118.10	0	5.36e ⁻⁵²	5.36e ⁻⁵² -5.36e ⁻⁵²	<.001
	White	389.38	0	1.27e ¹⁶⁹	1.27e ¹⁶⁹ -1.27e ¹⁶⁹	<.001
	Multiracial	422.26	0	2.42e ¹⁸³	2.42e ¹⁸³ -2.42e ¹⁸³	<.001
	Biological sex (Male)	-154.03	0	1.28e ⁻⁶⁷	1.28e ⁻⁶⁷ -1.28e ⁻⁶⁷	<.001
Believers-Consistently Low	Intercept	40.09	0	2.57e ¹⁷	2.57e ¹⁷ -2.57e ¹⁷	<.001
	Experience	-4.97	0	6.93e ⁻⁴	6.93e ⁻⁴ -6.93e ⁻⁴	<.001
	Math Courses					
	1 or 2 Classes	-50.61	0	1.04e ⁻²²	1.04e ⁻²² -1.04e ⁻²²	<.001
	3-to-5 Classes	-52.59	0	1.45e ⁻²³	1.45e ⁻²³ -1.45e ⁻²³	<.001
	6+ Classes	-41.28	0	1.18e ⁻¹⁸	1.18e ⁻¹⁸ -1.18e ⁻¹⁸	<.001
	Math Content					

1 or 2 Classes	62.58	0	1.51e ²⁷	1.51e ²⁷ - 1.51e ²⁷	<.001
3-to-5 Classes	62.93	0	2.13e ²⁷	2.13e ²⁷ - 2.13e ²⁷	<.001
6+ Classes	293.17	0	2.09e ¹²⁷	2.09e ¹²⁷ - 2.09e ¹²⁷	<.001
Math Methods					
1 or 2 Classes	96.02	0	5.01e ⁴¹	5.01e ⁴¹ - 5.01e ⁴¹	<.001
3-to-5 Classes	-12.36	0	4.28e ⁻⁶	4.28e ⁻⁶ - 4.28e ⁻⁶	<.001
6+ Classes	-227.82	0	1.14e ⁻⁹⁹	1.14e ⁻⁹⁹ - 1.14e ⁻⁹⁹	<.001
Master's Degree	-182.14	0	7.87e ⁻⁸⁰	7.87e ⁻⁸⁰ - 7.87e ⁻⁸⁰	<.001
Hispanic	58.83	0	3.56e ²⁵	3.56e ²⁵ - 3.56e ²⁵	<.001
Black	52.92	0	9.61e ²²	9.61e ²² - 9.61e ²²	<.001
White	-127.41	0	4.65e ⁻⁵⁶	4.65e ⁻⁵⁶ - 4.65e ⁻⁵⁶	<.001
Multiracial	-22.00	0	2.78e ⁻¹⁰	2.78e ⁻¹⁰ - 2.78e ⁻¹⁰	<.001
Biological sex (Male)	156.99	0	1.51e ⁶⁸	1.51e ⁶⁸ - 1.51e ⁶⁸	<.001

The second model including teacher racial and ethnical demographic variables was a better fitting model compared to the first model ($\chi^2(12)=1007, p<.001$). However, no clear pattern in the relationship between these variables and classes emerged. Those that identified from a Hispanic background were considerably more likely to be in the Efficacious and Believers group, with incredibly large odds ratios (see Table 7; for parsimony, only results from model 3 are presented). Similar extreme odds ratios were observed across all estimates, calling into question the veracity of these outcomes (see Discussion). Extreme odds ratios are often the result of several predictors in a regression model and a small sample size that cannot provide enough information for unbiased estimates for each predictor (Nemes, Jonasson, Genell, & Steineck, 2009).

The third model with the additional biological sex predictor variable was a better fitting model compared to the second model ($\chi^2(3)=136, p<.001$). Male teachers were considerably less likely to be in the Controversial or Efficacious group compared to the Consistently Low group. In contrast, they were considerably more likely to be in the Believers group than female teachers. This model explained 77% of variance averaged across McFadden's, Cox and Snell's, and Nagelkerke's pseudo- R^2 metrics.

Classes predicting student outcomes. Multivariate analyses were conducted to assess how the different teacher groups impacted student outcomes. Since behavioral engagement and math performance were the only student outcomes exhibiting relationships with teacher variables in the structural equation models, these were the only student dependent variables. Class membership was the only independent variable. A single behavioral engagement summative index was calculated to simplify analyses.

Statistical and visual analyses were conducted to determine if the models met assumptions following multivariate regression analyses. Most assumptions were met with the exception of multivariate residual normality. Mahalanobis distance between the dependent variable residuals were plotted in a Q-Q plot. Most data points fell along the diagonal, but notable divergence was observed in the upper quantile, indicating some potential deviation from normality. A Shapiro-Wilk's test provided some corroborating evidence ($p<.001$). However, general linear models are often robust to violations of multivariate residual normality when the sample is sufficiently large; considering the large sample size of students used in this portion of the study (full sample, $N=3,550$), this was considered a non-issue and thus model results trustworthy.

First, an omnibus MANCOVA analysis was conducted to determine the presence of a multivariate pattern between the dependent and independent variables. A consistently significant effect was observed, Pillai's Trace=.03, $F(6,6338)=14.7$, $p<.001$, Wilk's $\Lambda=.97$, $F(6,6336)=14.7$, $p<.001$, Hotelling's Trace=.03, $F(6,6334)=14.7$, $p<.001$, Roy's Largest Root=.02, $F(3,3169)=20.2$, $p<.001$. Follow-up multivariate simple regression models with post-hoc comparisons were conducted for more specific results. The Controversial Class was set as the referent group since this group had the most discrepancy between beliefs. Inflated error rate due to multiple pairwise comparisons was controlled for using both the Bonferroni and Holm methods (Aickin & Gensler, 1996).

Table 8

Multivariate simple regression outcomes using class to predict behavioral engagement

Parameter	Estimate	SE	95% CI	Df	t	<i>p</i> _{unadjusted}	<i>p</i> _{Bonferroni}	<i>p</i> _{Holm}
Intercept	12.35	0.15	12.06, 12.65	151	82.33	<.001	--	--
Consistently Low [±]	-0.36	0.24	-0.82, 0.11	152	-1.50	0.14	--	--
Efficacious	0.41	0.23	-0.04, 0.87	150	1.79	0.08	--	--
Believers	0.23	0.28	-0.33, 0.78	150	0.80	0.42	--	--
Post hoc								
Parameter	Estimate	SE	95% CI	Df	t	<i>p</i> _{unadjusted}	<i>p</i> _{Bonferroni}	<i>p</i> _{Holm}
Consistently Low-Efficacious ^{±±}	-0.77	0.26	-1.29, -.26	150	-3.02	<.001	0.02	0.02
Consistently Low-Believers	-0.58	0.30	-1.18, 0.02	150	-1.93	0.05	0.32	0.27
Efficacious-Believers	0.19	0.30	-0.41, 0.79	150	0.64	0.52	1	0.85
Random Effects								
Parameter	SD	Variance						
Intercept	0.56	0.32						

Note. †Comparison group is Controversial group. The estimate here is a difference in means subtracting the Controversial mean from the other comparison group.

‡‡Remaining post-hoc comparisons not involving the Controversial group.

AIC=15362.97

Marginal R^2 =.01

Conditional R^2 =.13

Tables 8 and 9 present fixed- and random-effect estimates. For behavioral engagement, no group resulted in significant differences compared to the Controversial group. Post-hoc analyses revealed only one significant comparison between the Consistently Low and Efficacious groups. Teachers in the Efficacious were, on average, associated with greater behavioral engagement than their peers in the Consistently Low group, suggesting that higher efficacy and moderate implicit theory (the main distinguishing features between these two classes) were associated with greater behavioral engagement. Marginal and conditional R^2 estimates were .01 and .13, respectively.

Table 9

Multivariate simple regression outcomes using class to predict math performance

Parameter	Estimate	SE	95% CI	df	t	$p_{unadjusted}$	$p_{Bonferroni}$	p_{Holm}
Intercept	0.32	0.12	0.09, 0.56	157	2.76	.01	--	--
Consistently Low†	0.11	0.15	-0.19, 0.40	157	0.69	0.49	--	--
Efficacious	0.07	0.16	-0.25, 0.39	157	0.44	0.66	--	--
Believers	0.45	0.19	0.07, 0.82	158	2.33	0.02	--	--
Post hoc								
Parameter	Estimate	SE	95% CI	df	t	$p_{unadjusted}$	$p_{Bonferroni}$	p_{Holm}
Consistently Low-Efficacious‡‡	-0.07	0.16	-0.39, 0.26	157	0.69	0.49	1	1
Consistently Low-Believers	-0.45	0.19	-0.83, -0.07	158	-2.33	0.02	0.11	0.11

Efficacious-Believers	-0.38	0.19	-0.76, 0	158	-1.99	0.05	0.28	0.23
Random Effects								
Parameter	SD	Variance						
Intercept	0.70	0.49						

Note. [±]Comparison group is Controversial group. The estimate here is a difference in means subtracting the Controversial mean from the other comparison group.

^{±±}Remaining post-hoc comparisons not involving the Controversial group.

AIC=8890.30

Marginal R^2 =.02

Conditional R^2 =.41

Regarding math performance, no group resulted in significant differences compared to the Controversial group. Post-hoc analyses revealed one potentially significant comparison between the Consistently Low and Believers group; however, after controlling for multiple comparisons, this pairwise comparison was no longer significant. This indicated that, overall, no group of teachers resulted in better math performance. Despite no significant comparisons, marginal and conditional R^2 estimates were .02 and .41, respectively.

Chapter 5: Discussion

Teachers are pivotal figures who influence student engagement and learning (Hattie, 2008; You & Sharkey, 2009), especially in math. Through effective instruction, relational and communication skills, and modeling of expected behaviors, they can promote student academic success in school. A critical mechanism through which teachers may guide students to success is by engaging students in their academic work. A deeply engaged student is one that exhibits expected behaviors, develops a genuine interest in their work, and feels a sense of belonging and community with their teacher, classroom peers, and the school broadly. Previous work investigating teacher beliefs and behaviors that influence engagement and academic achievement—specifically, math achievement—has so far remained inconclusive, partly because much of this work has been done in theoretical siloes (Mujis & Reynolds, 2002; Polly et al., 2013). This study attempted to further clarify the relationship between teacher self-efficacy and their implicit theory of student math intelligence, and the instructional practices they deliver to increase students' engagement and learning in math. More specifically, it examined the degree to which teachers' self-reported instructional practice related to their self-efficacy and beliefs about the malleability of their students' math intelligence, and the subsequent influence on student engagement and math performance. Considering the teacher-level variables were self-report, any inferences drawn from this study are couched within a general theme of how teacher beliefs and perceptions of themselves, their practices, and students relate to student engagement and mathematics performance. Guiding this study was a theoretical framework that posited that beliefs may be relevant to student

engagement but that the teacher beliefs operate through the instructional practices they implement.

This framework was largely unsupported in this study. Several key relationships at the teacher- and student-level resulted in null findings. First, not all dimensions of engagement were related to math achievement. Second, the relationship between teacher factors—particularly between beliefs and behaviors—were not as strong as previous relationship and theory suggested. Finally, there was little evidence of direct effects from teachers to students. Each of these results and potential explanations are discussed below.

Affective, behavioral, and cognitive engagement were moderately-to-strongly correlated to one another, echoing past research and theory (Reschly, Appleton, & Christenson, 2007). The strong relationship between affective and cognitive engagement was expected, considering the strong link between cognitions and feelings (German & DeRubeis, 2015; Reschly & Christenson, 2006). In this study, affective engagement was measured through student self-report of their emotional reactions to the classroom and how the teacher responded. In other words, it was measured as an internal, subjective appraisal of the learning environment. Nurturing classroom environments—defined as one in which a teacher is responsive to students and reinforces a child’s inherent worth (Biglan, Flay, Embry, & Sandler, 2012; Irwin, Siddiqi, Hertzman, 2007)—allow students to explore their interests more freely and feel a greater sense of belonging, both of which result in students experiencing deeper engagement, motivation, and interest in their work, ala cognitive engagement (Brooks, Brooks, & Goldstein, 2012). In turn, a student that is cognitively engaged may also associate this internal positive appraisal of the educational

content with their learning environment. Thus, affective and cognitive engagement, both as internal appraisals of the learning environment, should be highly related.

Notwithstanding the association between affective and cognitive engagement, a student's interest in a topic or sense of belonging within a nurturing environment does not directly lead to better performance unless behavioral enactment (i.e., participation) is supported (Appleton, Christenson, & Furlong, 2008). This is perhaps why behavioral engagement was the only engagement domain that was significantly related to math performance. Indeed, previous research supports the link between indicators of behavioral engagement and student math performance (Durksen et al., 2017). This does not imply that affective or cognitive engagement are inconsequential. Since they are internal reactions to the learning environment, it is possible that behavioral engagement is a partial mediator between them and math performance. This relationship was not tested in this study, but it is possible that students need behavioral engagement to facilitate affective and cognitive engagement indirectly influencing performance.

Self vs Other-oriented Implicit Theory of Intelligence

Results pertaining to the associations between teacher-level variables and student outcomes were inconsistent with initial hypotheses. Only a teacher's implicit theory, arguably the more abstract and distal belief compared to instructional self-efficacy, was related to student engagement. More specifically, implicit theory was found to be positively associated with only one student engagement indicator: behavioral engagement. Importantly, this study used items assessing teachers' implicit theories about their students' capacity to grow intelligence, and not their own (as is commonly measured in the implicit theory literature). The distinction here between how researchers have

historically conceptualized and measured implicit theories of intelligence and how this study did so is critical and worth reviewing. As Dweck described in her popular book (2006), implicit theories can be general or domain-specific (e.g., pertaining to a particular skill or activity). Regardless, an individual's implicit theory is beholden to the universal principle; all individuals are subject to the same implicit belief—either we are fixed or grow within a given domain. In the case of this study, implicit theory was specific to the nature of math intelligence. However, even within Dweck's seminal work (2006), there is dissonance between this universal principle and the actual referent of items on measures of implicit theory. For example, on the *mindsetwork*® website (Mindset Assessments, 2020), several variations of implicit theory measures are available. Many contain items that refer to the self (e.g., "I like my work best when it makes me think hard", "To tell the truth, when I work hard, it makes me feel as though I'm not very smart") and thus are measuring a self-oriented mindset. In contrast, this study used items referring to the student (e.g., "Students have a certain amount of intelligence and they can't really do much to change it."), i.e., an other-oriented mindset. There is not yet specific research on if these two orientations differ but, conceptually, they might. A self-oriented implicit theory captures an individual's perception of their own failure and willingness to engage in challenges when failure is likely. Bandura (2001) described similar perceptions comprising self-efficacy in Social Cognitive Theory—outcome expectations and outcome expectancies. That is, self-efficacy and a self-oriented mindset exhibit some conceptual redundancy. And the extensive research base into self-efficacy is clear that an individual's efficacy beliefs do not have to be congruent with their perceptions of other's

efficacy. Applying the same logic to mindset, self-oriented and other-oriented mindsets might be distinguishable and the latter worth further study.

In truth, an other-oriented mindset resembles another well-studied educational phenomenon—teacher’s implicit expectations for students, i.e., the “Pygmalion Effect” (Chang, 2011). Implicit theory impacting student behavioral engagement is consistent with a long line of research examining the importance of teachers’ expectancies of student behavior and performance. Forty years ago researchers demonstrated that teachers’ expectations of student ability in reading, English language arts, component skills in mathematics, and verbal skills were all strongly positively correlated to student achievement in those domains in grades 1-4 (average $r=.696$; Crano & Mellon, 1978). Student achievement in one grade (e.g., grade 1) was positively correlated with teacher expectations in the following year (e.g., grade 2), indicating a cascading effect from expectation to achievement to further expectations. When teacher expectations are high, they are more likely to create conditions in which students thrive and grow (e.g., Bryk, Lee, & Holland, 1993; Treisman, 1992). In contrast, when teacher expectations are low—especially when implicitly informed by racial, ethnic, and gender biases (Tenenbaum & Ruck, 2007)—students may comply with those expectations, resulting in problem behaviors, poor performance, and a detrimental self-fulfilling prophecy that cascades into long-term outcomes.

This potential causal link between teacher expectations and student outcomes has been experimentally explored in recent research using the quality and intent of communication between teacher and student as a mediating mechanism (Thayer et al., 2018; Yeager et al., 2014). With structured communication of positive, high expectations,

teachers were able to increase students' work completion and quality (Yeager et al., 2014), as well as reduce problem behaviors indicative of low behavioral engagement and risk for dropout (Thayer et al., 2018). Through experimental manipulation, these two studies illustrate one critical component of the expectation-to-achievement relationship. However, findings on the link between teacher expectations and student performance have been inconsistent in the literature (Jussim & Harber, 2005). This could be due to the failure to measure important mechanisms by which expectations impact student outcomes (e.g., communication, modeled behaviors in the classroom). In contrast, such mechanisms have been studied within the implicit theory literature which represents how these two literature bases may overlap and compliment one another.

The mediation analyses using self-reported instructional effectiveness as a mediator were intended to account for one way in which teacher's other-oriented implicit beliefs may influence behavioral engagement. Results indicated no significant mediation effect when including instructional effectiveness as a mediator between implicit theory and behavioral engagement. Broadly, though, self-reported instructional effectiveness was positively associated with self-efficacy, perhaps because, like students' affective and cognitive engagement, self-report of instruction is an internal, subjective appraisal like self-efficacy. Teachers who perceive highly frequent use of effective instructional practices likely also perceive themselves as effective math teachers (Künsting, Neuber, & Lipowsky, 2016). Reciprocally, a higher sense of self-efficacy may inform their perceptions of their instructional effectiveness. Indeed, several years of corroborating research support the predictive relationship between self-efficacy and instruction (Zee & Koomen, 2016).

It is important to consider the mechanism by which teachers' other-oriented implicit theories would impact student behavioral engagement. Potential mediators could be construction of a growth promoting classroom environment (i.e., teachers with a growth mindset orientation about their students may include imagery and instructional materials that emphasize growth), verbal behavior (i.e., praise and recognition for specific behaviors, effort, and work persistence), and perhaps even previous lessons specifically on mindset (i.e., such as the lessons used in Hong & Lin-Siegler, 2012). Less proximal potential mediators between implicit theory and behavioral engagement include the general quality of student-teacher relationship and interactions and behavior modeling in the classroom (i.e., teacher adopts a growth mindset about their own work and models for their students; Haimovitz & Dweck, 2017). The extant literature offers limited studies examining the mechanisms by which social-cognitive factors, such as teachers' beliefs about their students, impact student outcomes (Seaton, 2018). Conducting analyses to identify mediators is recommended as an incredibly important line of work (Kazdin, 2007) and would be beneficial in further elucidating exactly how a teacher's implicit theory influences students.

An unexpected result in this study was the considerable variability in the indicators for teachers' implicit theory of student intelligence. Growth mindset has become a popular concept in education (e.g., nearly 80% endorse an incremental theory in Jones, Bryant, Snyder, & Malone, 2012) and other child-serving sectors, as well as disseminated regularly through modern day information outlets (e.g., social media, YouTube, podcasts). Ratings on these indicators were expected to be high, identifying that most teachers would endorse a growth mindset. It is possible that the slight change in

the target of the implicit theory (from self to student) resulted in increased variability among teachers. This brings the findings of this study closer to in extant literature that indicates teacher expectations can vary greatly depending on their own gender and racial/ethnic identification, as well as personal history (Tenenbaum & Ruck, 2007).

Although unexpected, these results suggest that teachers' other-oriented implicit theories remain a potential avenue for simple intervention. Given the popularity of growth mindset (Boaler, 2013), this concept can be used to generate teacher buy-in to aligned instructional and relational practices. Previous work has demonstrated that it possible to use the popularity of growth mindset to engage teachers in learning activities that produce real world impact in how they address mental health and academic needs in the classroom (Cook et al., in preparation; Seaton, 2018). Similarly, if students do succumb to the "Pygmalion Effect" and act in accordance with the expectations of their teachers, positively attuning teachers' implicit theories about their students could result in a cascade of improvements in behavioral engagement and math performance. Considering how relatively simple and cost-efficient some growth mindset interventions can be that target an individual's underlying implicit theory (see Paunesku et al., 2015 and Yeager et al., 2016 for examples), these interventions—with some adjustments to make them appropriate for adult educators—could be useful tools in conjunction with other individual and organizational professional development practices.

Surprisingly, instructional effectiveness was not related to any of the engagement domains. Based on correlations, instructional effectiveness evidenced no meaningful relationship to math performance. This finding stands in contradiction to previous research that has demonstrated a link between high quality, specific math instruction

strategies (e.g., Standards-based Instruction; Alliance, 2006) and math outcomes (Bodovski & Farkas, 2007; Kroesbergen, Van Luit, & Maas, 2004; Prast, Van de Weijer-Bergsma, Kroesbergen, & Van Luit, 2018; Thompson, 2009). This suggests that the practices being measured or the approach to measuring instructional practices may have not captured certain high-leverage practices. The findings could also be the result of the method used to assess instructional effectiveness, with self-report leading to overestimates among teachers in their frequency of using certain practices. Considering the high mean and skew in the instructional effectiveness sum variable, it is likely there simply was not enough variability to determine how different levels of instructional effectiveness influence student engagement. Given these potential measurement issues and inconsistency with previous research, findings related to instructional effectiveness should be interpreted with caution. Future research should continue to explore the development of measures that capture key high-leverage math practices that are linked to student learning. Measurement concerns are further discussed in the limitations section.

Implications for Research and Practice

This study was one of few that directly compared what teachers believe about themselves and their students and how they teach. In addition, it examined student outcomes across multiple domains of engagement and math performance. Thus, it attempted to provide a more integrated and holistic understanding of how all these variables associate with one another and student outcomes. Future research can and should continue to incorporate variables from different theoretical camps into single analyses to curtail unnecessary siloing of research and potential misunderstanding of

constructs and ideas when translating findings into actual practice. Interestingly, this study determined that teachers' implicit theories about their students' intelligences may be critical factors for student behavior and warrants continued investigation. This contrasts with findings from Sisk and colleagues (2018) demonstrating small mean associations between mindsets in students and achievement. It is possible that the importance of implicit theory differs between students reflecting upon themselves (self-belief) and teachers reflecting upon their students (other-beliefs). Immediate follow-up research studies to explore this concept is to first measure the degree of discrepancy that may and can exist between teachers self-oriented and other-oriented implicit beliefs. Conceptually, these two orientations to implicit theories should be reliably distinguishable from one another. If the research supports this distinction, the next series of studies would be to ascertain the various relations between these beliefs and teacher variables. Ideally, those teacher variables would be observable behaviors hypothesized to be mechanisms of belief transmission to their students, such as the content, quantity, quality, and form of their instruction and communication to students. In addition, student self- and other-oriented implicit theories can and should be measured pre- and post-instruction with teachers to determine if these putative teacher behavior mechanisms resulted in internal belief changes in students, as well as behavioral outcomes. Results from this series of studies would provide various further directions potentially including teacher belief change efforts.

Exploration of this other-oriented implicit theory belief in teachers should be cautious, though, when considered the potential implication of this work with culturally and linguistically diverse students. Consider, for example, teachers with a growth mindset

toward their students of color. Although upon initial review, this may appear to be supportive and empowering for these students, it could also be an instance in which teachers are adopting a student-centered perspective that ignores less apparent—but certainly influential—systemic, cultural, and generally societal barriers that have historically resulted in worse outcomes in the school system for these students (e.g., Larson et al., 2019). In instances when students still struggle, it creates the opportunity for causes to be seen within a student (i.e., not trying as hard as they might) and to perpetuate ongoing beliefs about students from certain marginalized groups. Educators need to be cautious when identifying when students have capacity to meet and exceed expectations set by teachers—thus, fulfilling the growth other-oriented implicit belief—and when that capacity is legitimately handicapped by barriers beyond the control of the student. This puts into practice a real consideration of the ecological system within which students operate (Bronfenbrenner, 1977) and works to simultaneously support individual student growth and autonomy while also removing environmental barriers.

The lack of association between instruction and student engagement and performance is critical for future work. Research on mathematics instruction is underdeveloped compared to other areas such as literacy (National Research Council, 2001). Mathematics instruction in the United States exists within a broad cultural and pedagogical battle between explicit instructional practices and constructivist (i.e., discovery) practices (Alfieri, Brooks, Aldrich, & Tenenbaum, 2011; Marzano, 2011). Proponents of explicit instruction argue that it is more effective in teaching students concrete procedural and conceptual skills (e.g., Kroesbergen, Van Luit, & Maas, 2004; Poncy, McCallum, & Schmitt, 2010). Proponents of a constructivist approach argue that

it can produce similarly academic outcomes while also boosting motivation and engagement (e.g., Hickey, Moore, & Pellegrino, 2001). Conceptual and procedural skills, as well as a “productive disposition” (including motivation and interest in mathematics), are all critical student outcomes (National Research Council, 2001). What Works Clearinghouse reviewed the available literature on effective mathematics practices, from narrow and specific strategies to broad classroom practice and environmental conditions, to determine how to boost these outcomes in students (Frye et al., 2013). Explicit and constructivist strategies both commonly presented minimal preliminary evidence. In this case, minimal evidence refers not *only* to the magnitude of these strategies but the quantity and consistency of the effect across studies, suggesting that more research is needed to identify commonly effective strategies that address both mathematics skills and disposition.

This study contributes to this continued exploration while also highlighting the need for further clarity. The strategies included in this study are best categorized as explicit instructional strategies, yet they evidence no impact on engagement or performance (based on the correlations). It is possible that, as Alfieri and colleagues (2011) suggested in their meta-analysis comparing explicit and constructivist strategies, a balance of both is needed to produce improvements in academic and engagement outcomes.

Limitations

Several limitations exist in this study. First, the study sample has a few weaknesses. It is geographically representative of only a few eastern and southern states

in the United States. Such findings may not generalize to other geographical and culture populations. In addition, the sample was missing a large proportion of data on teacher backgrounds, so it is unclear how differences in training and experiences lead to teachers adopting different beliefs and behaviors.

A second limitation involves the holdout validation procedure. Best practices in structural equation modeling include such validation procedures to avoid overfitting data and drawing inferences that do not generalize well to a whole population. However, to create the split samples, the entire sample was split at the teacher-level. This still resulted in many students in the test set but shrunk the teacher sample size which may have hindered findings. This is particularly true regarding the full mediation model as that model was not able to be identified in the test set.

A third limitation is the lack of data on students' prior teachers. A worthy research question is to examine how teacher beliefs and behaviors longitudinally impact student engagement and math outcomes. Similarly, the lack of a prior achievement variable which likely influences a student's math engagement and performance is a notable limitation.

A fourth limitation is the exclusion of student demographic variables in the analyses, especially prior achievement. These were intentionally excluded for a couple reasons. Demographic data (e.g., racial/ethnic identity, IEP status, biological sex, socioeconomic status) were excluded to keep the analyses focused on the key variables of interest while also simplifying models to increase the likelihood of convergence. Racial identity, socioeconomic status, and biological sex have all demonstrated associations with student engagement, even after controlling for one another (Chavous, Rivas-Drake,

Smalls, Griffin, & Cogburn, 2008; Johnson, Crosnoe, & Elder Jr, 2001). These effects are likely present within this sample and interpretation of results should consider their omission. Prior achievement has been linked to later mathematics performance as well as engagement (DiPerna, Volpe, & Elliott, 2005). Although prior achievement data was available for this sample, it was only available for a subset of students (fifth grade students in Wave 2 that participated as fourth grade students in Wave 1) and missing for the remaining students. Its position as an exogenous variable precluded use of maximum likelihood to estimate this variable's effects, thus heavily limiting the sample size. Future studies should incorporate it as it is one of the strongest predictors of future achievement and, considering the reciprocal nature between prior student achievement and teacher expectations Crano and Mellon (1978) uncovered, it may also inform teachers' implicit theories about student intelligence.

A fifth limitation is a potential mismatch between research question and methodology. Specifically, research question three was focused on the identification of various profiles of teachers but this profiling question was raised as a way to capture the *interaction* between teacher beliefs and behaviors. Latent profile analysis is a method to capture a person-centered perspective on these variables but does not explicitly test the interaction between these variables and uncover how the effect magnitude of one or more influences the effect magnitude of another. Incorporating a latent interaction between the teacher beliefs and instructional effectiveness within the multi-level SEMs may be a better methodology to explicitly capture this hypothesized dependency than the profile method incorporated this study.

The last and most prominent limitation is the dataset itself, and more specifically, the way in which certain variables were measured. It seems an unlikely coincidence that the cross-level interaction between teacher implicit theory and behavioral engagement—the two latent constructs with the best overall measurement model and reliability at the teacher and student level, respectively—was the only interaction to demonstrate a statistically significant relationship. The remaining latent variables may have suffered from construct under-representativeness, especially those at the student level since they included only three indicators. Affective engagement is a multi-faceted concept that incorporates more than a student's report of how a teacher responds to their emotional state. Missing from this construct is a student's overall sense of belonging in that classroom (Reschly, Appleton, & Christenson, 2007). Only one item captured a student's perception of the classroom ("This math class is a happy place for me to be"), and its stem limited student response to their perception of happiness versus other emotional states. Cognitive engagement is another multi-faced concept incorporating interest in the content, motivation, personal academic goals, perception of autonomy, and personal values about learning (Reschly, Appleton, & Christenson, 2007). The three indicators in this study captured only student interest in mathematics, leaving much of their cognitive engagement left unmodeled. Relationships between engagement and math performance, and engagement and teacher variables, may have been more apparent if more indicators capturing the totality of these constructed had been used for these latent constructs.

Moreover, this was a cross-sectional study and student engagement variables may have more delayed effects on math outcomes (Galla et al., 2014). Thus, higher engagement creates more opportunities to learn and grow in math over time. Yet, cross

sectional studies like this one are limited in their ability to examine longitudinal effects (Johnson, 2010), which could have changed the magnitude and significance of the relationships between the variables included in this study.

A final measurement consideration is that some research suggests that implicit measures of beliefs and behaviors capture a unique perspective compared to self-report measures and demonstrate strong predictive validity (Greenwald, Poehlman, Uhlmann, & Banaji, 2009). The measurement model for teachers' implicit theory was the strongest across all latent variable. One potential adjustment for future studies is to incorporate implicit measures of teacher and student variables to see if they demonstrate better measurement properties and association with target outcomes. For instructional effectiveness, a potential adjustment would be to substitute teacher self-reported instructional practices with direct observation. This would allow researchers to draw inferences more proximal to the behaviors in question without the intervening confound of teacher perceptions of their own behaviors.

Conclusion

Teachers are influential forces in student engagement and math outcomes. Different theoretical perspectives indicate different high-priority teacher-level variables for improving student outcomes. Teacher beliefs and instructional behaviors both represent target variables. By integrating and comparing these variables, we can refine our theories and concentrate our efforts on the teacher-level factors and student engagement indicators that appear to matter the most. Such research will advance our

understanding of student-teacher interactions and lead to improvements in strengthening this protective factor that leads to higher engagement and math ability.

References

- Aditomo, A. (2015). Students' Response to Academic Setback: 'Growth Mindset' as a Buffer Against Demotivation. *International Journal of Educational Psychology*, 4(2), 198-222.
- Aickin, M., & Gensler, H. (1996). Adjusting for multiple testing when reporting research results: the Bonferroni vs Holm methods. *American journal of public health*, 86(5), 726-728.
- Alfieri, L., Brooks, P. J., Aldrich, N. J., & Tenenbaum, H. R. (2011). Does discovery-based instruction enhance learning?. *Journal of educational psychology*, 103(1), 1.
- Alliance, E. (2006). Closing the achievement gap: Best practices in teaching mathematics. Retrieved March, 8, 2010.
- Allison, P. D. (2014, March). Measures of fit for logistic regression. In *SAS Global Forum, Washington, DC*.
- Anderman, E. M., Eccles, J. S., Yoon, K. S., Roeser, R., Wigfield, A., & Blumenfeld, P. (2001). Learning to value mathematics and reading: Relations to mastery and performance-oriented instructional practices. *Contemporary Educational Psychology*, 26(1), 76-95.
- Andersen, S. M., & Chen, S. (2002). The relational self: an interpersonal social-cognitive theory. *Psychological review*, 109(4), 619.
- Andersen, S. C., & Nielsen, H. S. (2016). Reading intervention with a growth mindset approach improves children's skills. *Proceedings of the National Academy of Sciences*, 113(43), 12111-12113.
- Anderson, E. S., & Keith, T. Z. (1997). A longitudinal test of a model of academic success for at-risk high school students. *The Journal of Educational Research*, 90(5), 259-268.
- Appleton, J. J., Christenson, S. L., & Furlong, M. J. (2008). Student engagement with school: Critical conceptual and methodological issues of the construct. *Psychology in the Schools*, 45(5), 369-386.
- Appleton, J. J., Christenson, S. L., Kim, D., & Reschly, A. L. (2006). Measuring cognitive and psychological engagement: Validation of the Student Engagement Instrument. *Journal of School Psychology*, 44(5), 427-445.
- Arbuckle, J. L. (1996). Full information estimation in the presence of incomplete data. *Advanced structural equation modeling: Issues and techniques*, 243, 277.
- Arlot, S., & Celisse, A. (2010). A survey of cross-validation procedures for model selection. *Statistics surveys*, 4, 40-79.
- Armitage, C. J., & Conner, M. (2001). Efficacy of the theory of planned behaviour: A meta-analytic review. *British journal of social psychology*, 40(4), 471-499.
- Attewell, P., & Domina, T. (2008). Raising the bar: Curricular intensity and academic performance. *Educational Evaluation and Policy Analysis*, 30(1), 51-71.
- Babayak, M. A. (2004). What you see may not be what you get: a brief, nontechnical introduction to overfitting in regression-type models. *Psychosomatic medicine*, 66(3), 411-421.

- Bacher-Hicks, A., Chin, M., Hill, H. C., & Staiger, D. O. (2015). Explaining teacher effects on achievement using measures from multiple research traditions. *Unpublished manuscript*.
- Bandura, A. (1969). Principles of behavior modification.
- Bandura, A. (1991). Social cognitive theory of self-regulation. *Organizational behavior and human decision processes*, 50(2), 248-287.
- Bandura, A. (2001). Social cognitive theory: An agentic perspective. *Annual Review of Psychology*, 52, 1-26.
- Bandura, A., Pastorelli, C., Barbaranelli, C., & Caprara, G. V. (1999). Self-efficacy pathways to childhood depression. *Journal of Personality and Social Psychology*, 76(2), 258.
- Bates, M. E. (2000). Integrating person-centered and variable-centered approaches in the study of developmental courses and transitions in alcohol use: Introduction to the special section. *Alcoholism: Clinical and Experimental Research*, 24(6), 878-881.
- Biglan, A., Flay, B. R., Embry, D. D., & Sandler, I. N. (2012). The critical role of nurturing environments for promoting human well-being. *American Psychologist*, 67(4), 257.
- Blackwell, L. S., Trzesniewski, K. H., & Dweck, C. S. (2007). Implicit theories of intelligence predict achievement across an adolescent transition: A longitudinal study and an intervention. *Child development*, 78(1), 246-263.
- Blazar, D., & Kraft, M. A. (2017). Teacher and teaching effects on students' attitudes and behaviors. *Educational evaluation and policy analysis*, 39(1), 146-170.
- Block, J. (1971). *Lives through time*. Psychology Press.
- Boaler, J. (2013, March). Ability and mathematics: The mindset revolution that is reshaping education. In *Forum* (Vol. 55, No. 1, pp. 143-152).
- Bodovski, K., & Farkas, G. (2007). Mathematics growth in early elementary school: The roles of beginning knowledge, student engagement, and instruction. *The Elementary School Journal*, 108(2), 115-130.
- Bong, M. (2009). Age-related differences in achievement goal differentiation. *Journal of Educational Psychology*, 101(4), 879.
- Bradshaw, C. P., Zmuda, J. H., Kellam, S. G., & Ialongo, N. S. (2009). Longitudinal impact of two universal preventive interventions in first grade on educational outcomes in high school. *Journal of educational psychology*, 101(4), 926.
- Brooks, R., Brooks, S., & Goldstein, S. (2012). The power of mindsets: Nurturing engagement, motivation, and resilience in students. In *Handbook of research on student engagement*(pp. 541-562). Springer, Boston, MA.
- Bronfenbrenner, U. (1977). Toward an experimental ecology of human development. *American psychologist*, 32(7), 513.
- Brophy, J. E. (1983). Research on the self-fulfilling prophecy and teacher expectations. *Journal of educational psychology*, 75(5), 631.
- Brophy, J. E., & Good, T. L. (1970). Teachers' communication of differential expectations for children's classroom performance: Some behavioral data. *Journal of educational psychology*, 61(5), 365.
- Brown, E. D. (2009). Persistence in the face of academic challenge for economically disadvantaged children. *Journal of Early Childhood Research*, 7(2), 173-184.

- Bryan, J. (2005). Fostering educational resilience and achievement in urban schools through school-family-community partnerships. *Professional School Counseling, 219-227*.
- Bryk, A. S., Lee, V. E., & Peter, B. Holland. 1993. *Catholic schools and the common good, 297-327*.
- Burman, P. (1989). A comparative study of ordinary cross-validation, v-fold cross-validation and the repeated learning-testing methods. *Biometrika, 76(3), 503-514*.
- Burnette, J. L., O'boyle, E. H., VanEpps, E. M., Pollack, J. M., & Finkel, E. J. (2013). Mind-sets matter: A meta-analytic review of implicit theories and self-regulation. *Psychological Bulletin, 139(3), 655*.
- Byrnes, J. P., & Miller, D. C. (2007). The relative importance of predictors of math and science achievement: An opportunity-propensity analysis. *Contemporary Educational Psychology, 32(4), 599-629*.
- Caprara, G. V., Barbaranelli, C., Steca, P., & Malone, P. S. (2006). Teachers' self-efficacy beliefs as determinants of job satisfaction and students' academic achievement: A study at the school level. *Journal of school psychology, 44(6), 473-490*.
- Chang, J. (2011). A Case Study of the "Pygmalion Effect": Teacher Expectations and Student Achievement. *International education studies, 4(1), 198-201*.
- Chard, D. J., Ketterlin-Geller, L. R., Jungjohann, K., & Baker, S. K. (2009). Evidence-Based Math Instruction. *Practical Handbook of School Psychology: Effective Practices for the 21st Century, 287*.
- Chavous, T. M., Rivas-Drake, D., Smalls, C., Griffin, T., & Cogburn, C. (2008). Gender matters, too: The influences of school racial discrimination and racial identity on academic engagement outcomes among African American adolescents. *Developmental psychology, 44(3), 637*.
- Christenson, S. L., Stout, K. E. & Pohl, A. (2012). Check & Connect: A comprehensive student engagement intervention: Implementing with fidelity. Minneapolis, MN: University of Minnesota, Institute on Community Integration.
- Clotfelter, C. T., Ladd, H. F., & Vigdor, J. L. (2007). Teacher credentials and student achievement: Longitudinal analysis with student fixed effects. *Economics of Education Review, 26(6), 673-682*.
- Collins, L. M., & Lanza, S. T. (2010). Latent class analysis and latent transition analysis. *Hoboken: John Wiley & Sons*.
- Common Core State Standards Initiative. (2010). Common Core State Standards for Mathematics. Washington, DC: National Governors Association Center for Best Practices and the Council of Chief State School Officers.
- Confrey, J., Castro-Filho, J., & Wilhelm, J. (2000). Implementation research as a means to link systemic reform and applied psychology in mathematics education. *Educational Psychologist, 35(3), 179-191*.
- Connell, J. P., & Wellborn, J. G. (1991). Competence, autonomy, and relatedness: A motivational analysis of self-system processes. In M. R. Gunnar & L. A. Sroufe (Eds.), *Self processes and development: The Minnesota symposia on child development, 23, 43-78*. Hillsdale, NJ: Erlbaum.

- Cook, C. R., Fiat, A., Larson, M., Daikos, C., Slemrod, T., Holland, E. A., ... & Renshaw, T. (2017). Positive Greetings at the Door: Evaluation of a Low-Cost, High-Yield Proactive Classroom Management Strategy. *Journal of Positive Behavior Interventions*, 1098300717753831.
- Crano, W. D., & Mellon, P. M. (1978). Causal influence of teachers' expectations on children's academic performance: A cross-lagged panel analysis. *Journal of Educational Psychology*, 70(1), 39.
- Davison, M. L., & Sharma, A. R. (1994). ANOVA and ANCOVA of pre-and post-test, ordinal data. *Psychometrika*, 59(4), 593-600.
- De Ayala, R. J. (2013). *The theory and practice of item response theory*. Guilford Publications.
- Diamond, A. (2010). The evidence base for improving school outcomes by addressing the whole child and by addressing skills and attitudes, not just content. *Early education and development*, 21(5), 780-793.
- DiPerna, J. C., Volpe, R. J., & Elliott, S. N. (2005). A model of academic enablers and mathematics achievement in the elementary grades. *Journal of School Psychology*, 43(5), 379-392.
- Domitrovich, C. E., Bradshaw, C. P., Greenberg, M. T., Embry, D., Poduska, J. M., & Jalongo, N. S. (2010). Integrated models of school-based prevention: Logic and theory. *Psychology in the Schools*, 47(1), 71-88.
- Durksen, T. L., Way, J., Bobis, J., Anderson, J., Skilling, K., & Martin, A. J. (2017). Motivation and engagement in mathematics: a qualitative framework for teacher-student interactions. *Mathematics Education Research Journal*, 29(2), 163-181.
- Dweck, C. S. (2006). *Mindset: The new psychology of success*. Random House Incorporated.
- Dweck, C. S. (2014a). Mindsets and math/science achievement.
- Dweck, C. (2014b). Teachers' Mindsets: "Every Student has Something to Teach Me" Feeling overwhelmed? Where did your natural teaching talent go? Try pairing a growth mindset with reasonable goals, patience, and reflection instead. It's time to get gritty and be a better teacher. *Educational Horizons*, 93(2), 10-15.
- Dweck, C. S., & Leggett, E. L. (1988). A social-cognitive approach to motivation and personality. *Psychological review*, 95(2), 256.
- Earp, B. D., & Trafimow, D. (2015). Replication, falsification, and the crisis of confidence in social psychology. *Frontiers in psychology*, 6, 621.
- El Khiyari, H., De Marsico, M., Abate, A. F., & Wechsler, H. (2012). Biometric interoperability across training, enrollment, and testing for face authentication. In *Biometric Measurements and Systems for Security and Medical Applications (BIOMS), 2012 IEEE Workshop on* (pp. 1-8). IEEE.
- Enders, C. K., & Bandalos, D. L. (2001). The relative performance of full information maximum likelihood estimation for missing data in structural equation models. *Structural equation modeling*, 8(3), 430-457.
- Esparza, J., Shumow, L., & Schmidt, J. A. (2014). Growth Mindset of Gifted Seventh Grade Students in Science. *NCSSMST Journal*, 19(1), 6-13.
- Everingham, Y. L., Gyuris, E., & Connolly, S. R. (2017). Enhancing student engagement to positively impact mathematics anxiety, confidence and achievement for

- interdisciplinary science subjects. *International Journal of Mathematical Education in Science and Technology*, 48(8), 1153-1165.
- Farkas, G. (2003). Racial disparities and discrimination in education: What do we know, how do we know it, and what do we need to know? *Teachers College Record*, 105(6), 1119–1146.
- Festinger, L. (1962). Cognitive dissonance. *Scientific American*, 207(4), 93-106.
- Finn, J. D. (1989). Withdrawing from school. *Review of educational research*, 59(2), 117-142.
- Finn, J. D., & Rock, D. A. (1997). Academic success among students at risk for school failure. *Journal of applied psychology*, 82(2), 221.
- Finn, J. D., & Zimmer, K. S. (2012). Student engagement: What is it? Why does it matter?. In *Handbook of research on student engagement* (pp. 97-131). Springer US.
- Flink, C., Boggiano, A. K., & Barrett, M. (1990). Controlling teaching strategies: Undermining children's self-determination and performance. *Journal of Personality and social Psychology*, 59(5), 916.
- Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of educational research*, 74(1), 59-109.
- Froiland, J. M., & Davison, M. L. (2014). Parental expectations and school relationships as contributors to adolescents' positive outcomes. *Social Psychology of Education*, 17(1), 1-17.
- Frye, D., Baroody, A. J., Burchinal, M., Carver, S. M., Jordan, N. C., & McDowell, J. (2013). Teaching Math to Young Children. Educator's Practice Guide. What Works Clearinghouse. NCEE 2014-4005. *What Works Clearinghouse*.
- Fung, F., Tan, C. Y., & Chen, G. (2018). Student engagement and mathematics achievement: Unraveling main and interactive effects. *Psychology in the Schools*, 55(7), 815-831.
- Furey, T. S., Cristianini, N., Duffy, N., Bednarski, D. W., Schummer, M., & Haussler, D. (2000). Support vector machine classification and validation of cancer tissue samples using microarray expression data. *Bioinformatics*, 16(10), 906-914.
- Galla, B. M., Wood, J. J., Tsukayama, E., Har, K., Chiu, A. W., & Langer, D. A. (2014). A longitudinal multilevel model analysis of the within-person and between-person effect of effortful engagement and academic self-efficacy on academic performance. *Journal of School Psychology*, 52(3), 295-308.
- Geiser, C., & Wurpts, I. C. (2014). Is adding more indicators to a latent class analysis beneficial or detrimental? Results of a Monte Carlo study. *Frontiers in Psychology: Quantitative Psychology and Measurement*, 5.
- German, R. E., & DeRubeis, R. J. (2015). Cognitive-Behavioral Psychotherapy. *Encyclopedia of Mental Health*, 297.
- Gersten, R., Chard, D. J., Jayanthi, M., Baker, S. K., Morphy, P., & Flojo, J. (2009). Mathematics Instruction for Students with Learning Disabilities or Difficulty Learning Mathematics: A Synthesis of the Intervention Research. *Center on instruction*.

- Gilman, R., Meyers, J., & Perez, L. (2004). Structured extracurricular activities among adolescents: Findings and implications for school psychologists. *Psychology in the Schools, 41*(1), 31-41.
- Goldstein, J. S., Little, S. G., & Akin-Little, K. A. (2003). Absenteeism: A review of the literature and school psychology's role. *The California School Psychologist, 8*(1), 127-139.
- Good, C., Aronson, J., & Inzlicht, M. (2003). Improving adolescents' standardized test performance: An intervention to reduce the effects of stereotype threat. *Journal of Applied Developmental Psychology, 24*(6), 645-662.
- Goodenow, C. (1991, April). The sense of belonging and its relationship to academic motivation among pre- and early adolescent students. Paper presented at the annual meeting of the American Educational Research Association, Chicago, IL. (ERIC Document Reproduction Service No. ED335151).
- Grant, H., & Dweck, C. S. (2003). Clarifying achievement goals and their impact. *Journal of personality and social psychology, 85*(3), 541.
- Greenwald, A. G., Poehlman, T. A., Uhlmann, E. L., & Banaji, M. R. (2009). Understanding and using the Implicit Association Test: III. Meta-analysis of predictive validity. *Journal of personality and social psychology, 97*(1), 17.
- Guo, Y., Connor, C. M., Yang, Y., Roehrig, A. D., & Morrison, F. J. (2012). The effects of teacher qualification, teacher self-efficacy, and classroom practices on fifth graders' literacy outcomes. *The Elementary School Journal, 113*(1), 3-24.
- Gutman, L. M., Sameroff, A. J., & Eccles, J. S. (2002). The academic achievement of African American students during early adolescence: An examination of multiple risk, promotive, and protective factors. *American journal of community psychology, 30*(3), 367-399.
- Haimovitz, K., & Dweck, C. S. (2017). The origins of children's growth and fixed mindsets: New research and a new proposal. *Child development, 88*(6), 1849-1859.
- Haimovitz, K., Wormington, S. V., & Corpus, J. H. (2011). Dangerous mindsets: How beliefs about intelligence predict motivational change. *Learning and Individual Differences, 21*(6), 747-752.
- Hamre, B. K., & Pianta, R. C. (2001). Early teacher-child relationships and the trajectory of children's school outcomes through eighth grade. *Child development, 72*(2), 625-638.
- Handelsman, M. M., Briggs, W. L., Sullivan, N., & Towler, A. (2005). A measure of college student course engagement. *The Journal of Educational Research, 98*(3), 184-192.
- Harden, J. J. (2011). A bootstrap method for conducting statistical inference with clustered data. *State Politics & Policy Quarterly, 11*(2), 223-246.
- Hartley, M. T. (2011). Examining the relationships between resilience, mental health, and academic persistence in undergraduate college students. *Journal of American College Health, 59*(7), 596-604.
- Harwell, M., & LeBeau, B. (2010). Student eligibility for a free lunch as an SES measure in education research. *Educational Researcher, 39*(2), 120-131.

- Hattie, J. (2008). Visible learning: A synthesis of over 800 meta-analyses relating to achievement. routledge.
- Heck, R. H., & Thomas, S. L. (2015). An introduction to multilevel modeling techniques: MLM and SEM approaches using Mplus. Routledge.
- Hickey, D. T., Moore, A. L., & Pellegrino, J. W. (2001). The motivational and academic consequences of elementary mathematics environments: Do constructivist innovations and reforms make a difference?. *American Educational Research Journal*, 38(3), 611-652.
- Hickman, Fu, & Hill (2012). Creation and dissemination of Upper-elementary Mathematics Assessment Modules (Report No. 1). Educational Testing Service.
- Hill, H. C., Rowan, B., & Ball, D. L. (2005). Effects of teachers' mathematical knowledge for teaching on student achievement. *American educational research journal*, 42(2), 371-406.
- Hill, P. W., & Rowe, K. J. (1996). Multilevel modelling in school effectiveness research. *School effectiveness and school improvement*, 7(1), 1-34.
- Hochanadel, A., & Finamore, D. (2015). Fixed and growth mindset in education and how grit helps students persist in the face of adversity. *Journal of International Education Research*, 11(1), 47.
- Hong, H. Y., & Lin-Siegler, X. (2012). How learning about scientists' struggles influences students' interest and learning in physics. *Journal of Educational Psychology*, 104, 469-485.
- Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural equation modeling: a multidisciplinary journal*, 6(1), 1-55.
- Jackson, A. P., Smith, S. A., & Hill, C. L. (2003). Academic persistence among Native American college students. *Journal of College Student Development*, 44(4), 548-565.
- Jayanthi, M., Gersten, R., & Baker, S. (2008). Mathematics Instruction for Students with Learning Disabilities or Difficulty Learning Mathematics: A Guide for Teachers. *Center on Instruction*.
- Jitendra, A. K., Lein, A. E., Im, S. H., Alghamdi, A. A., Hefte, S. B., & Mouanoutoua, J. (2018). Mathematical interventions for secondary students with learning disabilities and mathematics difficulties: A meta-analysis. *Exceptional Children*, 84(2), 177-196.
- Johnson, S. L. (2010). A question of time: Cross-sectional versus longitudinal study designs. *Pediatrics in review*, 31(6).
- Johnson, M. K., Crosnoe, R., & Elder Jr, G. H. (2001). Students' attachment and academic engagement: The role of race and ethnicity. *Sociology of education*, 318-340.
- Jones, B. D., Bryant, L. H., Snyder, J. D., & Malone, D. (2012). Preservice and inservice teachers' implicit theories of intelligence. *Teacher Education Quarterly*, 39(2), 87-101.
- Jussim, L., & Harber, K. D. (2005). Teacher expectations and self-fulfilling prophecies: Knowns and unknowns, resolved and unresolved controversies. *Personality and social psychology review*, 9(2), 131-155.

- Kastberg, D., Chan, J.Y., and Murray, G. (2016). *Performance of U.S. 15-Year-Old Students in Science, Reading, and Mathematics Literacy in an International Context: First Look at PISA 2015* (NCES 2017-048). U.S. Department of Education. Washington, DC: National Center for Education Statistics. Retrieved [5/31/2018] from <http://nces.ed.gov/pubsearch>.
- Kazdin, A. E. (2007). Mediators and mechanisms of change in psychotherapy research. *Annu. Rev. Clin. Psychol.*, 3, 1-27.
- Keselman, H. J., Algina, J., Kowalchuk, R. K., & Wolfinger, R. D. (1999). The analysis of repeated measurements: A comparison of mixed-model Satterthwaite F tests and a nonpooled adjusted degrees of freedom multivariate test. *Communications in Statistics-Theory and Methods*, 28(12), 2967-2999.
- Kroesbergen, E. H., Van Luit, J. E., & Maas, C. J. (2004). Effectiveness of explicit and constructivist mathematics instruction for low-achieving students in the Netherlands. *The Elementary School Journal*, 104(3), 233-251.
- Kunter, M., Klusmann, U., Baumert, J., Richter, D., Voss, T., & Hachfeld, A. (2013). Professional competence of teachers: effects on instructional quality and student development. *Journal of Educational Psychology*, 105(3), 805.
- Künsting, J., Neuber, V., & Lipowsky, F. (2016). Teacher self-efficacy as a long-term predictor of instructional quality in the classroom. *European Journal of Psychology of Education*, 31(3), 299-322.
- Lambert, M. C., Cartledge, G., Heward, W. L., & Lo, Y. Y. (2006). Effects of response cards on disruptive behavior and academic responding during math lessons by fourth-grade urban students. *Journal of Positive Behavior Interventions*, 8(2), 88-99.
- Land, M. L. (1979). Low-inference variables of teacher clarity: Effects on student concept learning. *Journal of Educational Psychology*, 71(6), 795.
- Larson, K. E., Bottiani, J. H., Pas, E. T., Kush, J. M., & Bradshaw, C. P. (2019). A multilevel analysis of racial discipline disproportionality: A focus on student perceptions of academic engagement and disciplinary environment. *Journal of school psychology*, 77, 152-167.
- Leggett, E. L. (1985). Children's entity and incremental theories of intelligence: Relationships to achievement behavior. In *Annual Meeting of the Eastern Psychological Association, Boston*.
- Lein, A. E., Jitendra, A. K., Starosta, K. M., Dupuis, D. N., Hughes-Reid, C. L., & Star, J. R. (2016). Assessing the relation between seventh-grade students' engagement and mathematical problem solving performance. *Preventing School Failure: Alternative Education for Children and Youth*, 60(2), 117-123.
- Leon, J., Medina-Garrido, E., & Núñez, J. L. (2017). Teaching quality in math class: The development of a scale and the analysis of its relationship with engagement and achievement. *Frontiers in psychology*, 8, 895.
- Maas, C. J., & Hox, J. J. (2005). Sufficient sample sizes for multilevel modeling. *Methodology: European Journal of Research Methods for the Behavioral and Social Sciences*, 1(3), 86.

- MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological methods, 1*(2), 130.
- Mahatmya, D., Lohman, B. J., Matjasko, J. L., & Farb, A. F. (2012). Engagement across developmental periods. In *Handbook of research on student engagement* (pp. 45-63). Springer US.
- Marsh, H. W., Lüdtke, O., Trautwein, U., & Morin, A. J. (2009). Classical latent profile analysis of academic self-concept dimensions: Synergy of person-and variable-centered approaches to theoretical models of self-concept. *Structural Equation Modeling, 16*(2), 191-225.
- Martin, A. J. (2006). The relationship between teachers' perceptions of student motivation and engagement and teachers' enjoyment of and confidence in teaching. *Asia-Pacific Journal of Teacher Education, 34*(1), 73-93.
- Martin, A. J., & Marsh, H. W. (2006). Academic resilience and its psychological and educational correlates: A construct validity approach. *Psychology in the Schools, 43*, 267-281.
- Martin, A. J. (2007). Examining a multidimensional model of student motivation and engagement using a construct validation approach. *British Journal of Educational Psychology, 77*(2), 413-440.
- Martin, N. K., Sass, D. A., & Schmitt, T. A. (2012). Teacher efficacy in student engagement, instructional management, student stressors, and burnout: A theoretical model using in-class variables to predict teachers' intent-to-leave. *Teaching and Teacher Education, 28*(4), 546-559.
- Maruyama, G. (1997). Basics of structural equation modeling. Sage.
- Marzano, R. J. (2011). The perils and promises of discovery learning.
- Maxwell, S. E., Lau, M. Y., & Howard, G. S. (2015). Is psychology suffering from a replication crisis? What does "failure to replicate" really mean?. *American Psychologist, 70*(6), 487.
- McFarland, J., Hussar, B., de Brey, C., Snyder, T., Wang, X., Wilkinson-Flicker, S., ... & Bullock Mann, F. (2017). The Condition of Education 2017. NCES 2017-144. *National Center for Education Statistics*.
- McNeely, C., & Falci, C. (2004). School connectedness and the transition into and out of health-risk behavior among adolescents: A comparison of social belonging and teacher support. *Journal of school health, 74*(7), 284-292.
- McNeish, D., An, J., & Hancock, G. R. (2018). The thorny relation between measurement quality and fit index cutoffs in latent variable models. *Journal of personality assessment, 100*(1), 43-52.
- Measures of Effective Teaching: 1 - Study Information. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 2018-09-19. <https://doi.org/10.3886/ICPSR34771.v3>
- Midgley, C., Feldlaufer, H., & Eccles, J. S. (1989). Change in teacher efficacy and student self-and task-related beliefs in mathematics during the transition to junior high school. *Journal of educational Psychology, 81*(2), 247.
- Mindset Assessments. (n.d.). Retrieved July 19, 2020, from <https://www.mindsetworks.com/assess/>

- Mojavezi, A., & Tamiz, M. P. (2012). The impact of teacher self-efficacy on the students' motivation and achievement. *Theory and Practice in Language Studies*, 2(3), 483.
- Mujis, D., & Reynolds, D. (2002). Teachers' beliefs and behaviors: What really matters?. *The Journal of Classroom Interaction*, 3-15.
- Mullis, I. V. S., Martin, M. O., Foy, P., & Hooper, M. (2016). *TIMSS 2015 International Results in Mathematics*. Retrieved from Boston College, TIMSS & PIRLS International Study
- Murdock, T. B., & Miller, A. (2003). Teachers as sources of middle school students' motivational identity: Variable-centered and person-centered analytic approaches. *The Elementary School Journal*, 103(4), 383-399.
- Murray, H. G. (1983). Low-inference classroom teaching behaviors and student ratings of college teaching effectiveness. *Journal of Educational Psychology*, 75(1), 138.
- Muthén, L.K. & Muthén, B.O. (2018). Mplus User's Guide. Eighth Edition. Los Angeles, CA: Muthén & Muthén.
- National Assessment of Educational Progress. Retrieved October 20, 2018, from <https://nces.ed.gov/nationsreportcard/about/>.
- National Center for Education Statistics. (2015). *National Assessment of Educational Progress: Mathematics*. Washington, D.C.: National Center for Education Statistics, Institute of Education Sciences, U.S. Dept. of Education.
- National Research Council. (2001). *Adding it up: Helping children learn mathematics*. J.Kilpatrick, J. Swafford, and B.Findell (Eds.). Mathematics Learning Study Committee, Center for Education, Division of Behavioral and Social Sciences and Education. Washington, DC: National Academy Press.
- National Research Council and Institute of Medicine of the National Academies. (2004). *Engaging schools: Fostering high school students' motivation to learn*. Washington DC: The National Academies Press.
- National Science Foundation (2010). Science and engineering indicators. Retrieved July 7, 2018, from <http://www.nsf.gov/statistics/seind10/>.
- Nemes, S., Jonasson, J. M., Genell, A., & Steineck, G. (2009). Bias in odds ratios by logistic regression modelling and sample size. *BMC medical research methodology*, 9(1), 56.
- Nicpon, M. F., Huser, L., Blanks, E. H., Sollenberger, S., Befort, C., & Kurpius, S. E. R. (2006). The relationship of loneliness and social support with college freshmen's academic performance and persistence. *Journal of College Student Retention: Research, Theory & Practice*, 8(3), 345-358.
- Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural equation modeling*, 14(4), 535-569.
- Open Science Collaboration. (2015). Estimating the reproducibility of psychological science. *Science*, 349(6251).
- Park, D., Gunderson, E. A., Tsukayama, E., Levine, S. C., & Beilock, S. L. (2016). Young children's motivational frameworks and math achievement: Relation to teacher-reported instructional practices, but not teacher theory of intelligence. *Journal of Educational Psychology*, 108(3), 300.

- Paunesku, D., Walton, G. M., Romero, C., Smith, E. N., Yeager, D. S., & Dweck, C. S. (2015). Mind-set interventions are a scalable treatment for academic underachievement. *Psychological science*, 26(6), 784-793.
- Peltier, G. L., Laden, R., & Matranga, M. (2000). Student persistence in college: A review of research. *Journal of College Student Retention: Research, Theory & Practice*, 1, 357-375.
- Perkins-Gough, D. (2013). The significance of grit: A conversation with Angela Lee Duckworth. *Educational Leadership*, 71, 14-20.
- Petersen, J., Bandeen-Roche, K., Budtz-Jørgensen, E., & Larsen, K. G. (2012). Predicting latent class scores for subsequent analysis. *Psychometrika*, 77(2), 244-262.
- Polly, D., McGee, J. R., Wang, C., Lambert, R. G., Pugalee, D. K., & Johnson, S. (2013). The association between teachers' beliefs, enacted practices, and student learning in mathematics. *Mathematics educator*, 22(2), 11-30.
- Poncy, B. C., McCallum, E., & Schmitt, A. J. (2010). A comparison of behavioral and constructivist interventions for increasing math-fact fluency in a second-grade classroom. *Psychology in the Schools*, 47(9), 917-930.
- Prast, E. J., Van de Weijer-Bergsma, E., Kroesbergen, E. H., & Van Luit, J. E. (2018). Differentiated instruction in primary mathematics: Effects of teacher professional development on student achievement. *Learning and Instruction*, 54, 22-34.
- R Core Team (2017). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL <https://www.R-project.org/>.
- Ramirez, G., Gunderson, E. A., Levine, S. C., & Beilock, S. L. (2013). Math anxiety, working memory, and math achievement in early elementary school. *Journal of Cognition and Development*, 14(2), 187-202.
- Rattan, A., Good, C., & Dweck, C. S. (2012). "It's ok—Not everyone can be good at math": Instructors with an entity theory comfort (and demotivate) students. *Journal of Experimental Social Psychology*, 48(3), 731-737.
- Reeve, J. (2012). A self-determination theory perspective on student engagement. In *Handbook of research on student engagement* (pp. 149-172). Springer, Boston, MA.
- Refaeilzadeh, P., Tang, L., & Liu, H. (2009). Cross-validation. In *Encyclopedia of database systems* (pp. 532-538). Springer US.
- Reschly, A., & Christenson, S. L. (2006). Prediction of dropout among students with mild disabilities: A case for the inclusion of student engagement variables. *Remedial and Special Education*, 27, 276-292.
- Reschly, A. L., Appleton, J. J., & Christenson, S. L. (2007). Student engagement at school and with learning: Theory and interventions. *NASP Communiqué*, 35(8), 18-20.
- Reschly, A. L., & Christenson, S. L. (2012). Jingle, jangle, and conceptual haziness: Evolution and future directions of the engagement construct. In *Handbook of research on student engagement* (pp. 3-19). Springer US.
- Reschly, A., Pohl, A. J., Christenson, S. L., & Appleton, J. J. (2017). Engaging Adolescents in Secondary Schools. *School Mental Health Services for Adolescents*, 45.

- Reyes, M. R., Brackett, M. A., Rivers, S. E., White, M., & Salovey, P. (2012). Classroom emotional climate, student engagement, and academic achievement. *Journal of educational psychology, 104*(3), 700.
- Rhoades, L., & Eisenberger, R. (2002). Perceived organizational support: a review of the literature. *Journal of applied psychology, 87*(4), 698.
- Roberts, S., & Pashler, H. (2000). How persuasive is a good fit? A comment on theory testing. *Psychological review, 107*(2), 358.
- Ross, J. A., & Gray, P. (2006). School leadership and student achievement: The mediating effects of teacher beliefs. *Canadian Journal of Education/Revue canadienne de l'éducation, 798-822*.
- Scott, M. J., & Ghinea, G. (2014). On the domain-specificity of mindsets: The relationship between aptitude beliefs and programming practice. *IEEE Transactions on Education, 57*(3), 169-174.
- Shernoff, D. J., Csikszentmihalyi, M., Schneider, B., & Shernoff, E. S. (2014). Student engagement in high school classrooms from the perspective of flow theory. In *Applications of Flow in Human Development and Education* (pp. 475-494). Springer Netherlands.
- Schunk, D. H., & Mullen, C. A. (2012). Self-efficacy as an engaged learner. In *Handbook of research on student engagement* (pp. 219-235). Springer, Boston, MA.
- Seaton, F. S. (2018). Empowering teachers to implement a growth mindset. *Educational Psychology in Practice, 34*(1), 41-57.
- Siegle, D., & McCoach, D. B. (2007). Increasing student mathematics self-efficacy through teacher training. *Journal of Advanced Academics, 18*(2), 278-312.
- Sisk, V. F., Burgoyne, A. P., Sun, J., Butler, J. L., & Macnamara, B. N. (2018). To What Extent and Under Which Circumstances Are Growth Mind-Sets Important to Academic Achievement? Two Meta-Analyses. *Psychological science, 0956797617739704*.
- Skinner, E. A., & Belmont, M. J. (1993). Motivation in the classroom: Reciprocal effects of teacher behavior and student engagement across the school year. *Journal of educational psychology, 85*(4), 571.
- Stajkovic, A. D., & Luthans, F. (1998). Social cognitive theory and self-efficacy: Goin beyond traditional motivational and behavioral approaches. *Organizational dynamics, 26*(4), 62-74.
- Stickney, E. M., Sharp, L. B., & Kenyon, A. S. (2012). Technology-enhanced assessment of math fact automaticity: Patterns of performance for low-and typically achieving students. *Assessment for Effective Intervention, 37*(2), 84-94.
- Sugai, G., & Simonsen, B. (2012). Positive behavioral interventions and supports: History, defining features, and misconceptions. *Center for PBIS & Center for Positive Behavioral Interventions and Supports, University of Connecticut, 14*.
- Tenenbaum, H. R., & Ruck, M. D. (2007). Are teachers' expectations different for racial minority than for European American students? A meta-analysis. *Journal of educational psychology, 99*(2), 253.
- Teven, J. J., & McCroskey, J. C. (1997). The relationship of perceived teacher caring with student learning and teacher evaluation. *Communication Education, 46*(1), 1-9.

- Thayer, A. J., Cook, C. R., Fiat, A. E., Bartlett-Chase, M. N., & Kember, J. M. (2018). Wise Feedback as a Timely Intervention for At-Risk Students Transitioning Into High School. *School Psychology Review, 47*(3), 275-290.
- Thompson, C. J. (2009). Preparation, practice, and performance: An empirical examination of the impact of Standards-based Instruction on secondary students' math and science achievement. *Research in Education, 81*(1), 53-62.
- Treisman, U. (1992). Studying students studying calculus: A look at the lives of minority mathematics students in college. *The College Mathematics Journal, 23*(5), 362-372.
- Trends in International Mathematics and Science Study (TIMSS) - Overview. Retrieved October 20, 2018, from <https://nces.ed.gov/timss/>.
- Tripod® (2018). Retrieved October 13, 2018, from <https://tripoded.com/>.
- Valentiner, D. P., Mounts, N. S., Durik, A. M., & Gier-Lonsway, S. L. (2011). Shyness mindset: Applying mindset theory to the domain of inhibited social behavior. *Personality and individual differences, 50*(8), 1174-1179.
- Van Ryzin, M. J. (2011). Protective factors at school: Reciprocal effects among adolescents' perceptions of the school environment, engagement in learning, and hope. *Journal of Youth and Adolescence, 40*(12), 1568-1580.
- Voight, A., Hanson, T., O'Malley, M., & Adekanye, L. (2015). The Racial School Climate Gap: Within-School Disparities in Students' Experiences of Safety, Support, and Connectedness. *American journal of community psychology, 56*(3-4), 252-267.
- Wang, M. T., & Eccles, J. S. (2013). School context, achievement motivation, and academic engagement: A longitudinal study of school engagement using a multidimensional perspective. *Learning and Instruction, 28*, 12-23.
- Wolters, C. A., & Pintrich, P. R. (1998). Contextual differences in student motivation and self-regulated learning in mathematics, English, and social studies classrooms. *Instructional science, 26*(1-2), 27-47.
- Yeager, D. S., Purdie-Vaughns, V., Garcia, J., Apfel, N., Brzustoski, P., Master, A., ... & Cohen, G. L. (2014). Breaking the cycle of mistrust: Wise interventions to provide critical feedback across the racial divide. *Journal of Experimental Psychology: General, 143*(2), 804.
- Yeager, D. S., Romero, C., Paunesku, D., Hulleman, C. S., Schneider, B., Hinojosa, C., ... & Trott, J. (2016). Using design thinking to improve psychological interventions: The case of the growth mindset during the transition to high school. *Journal of educational psychology, 108*(3), 374.
- Yeager, D. S., & Walton, G. M. (2011). Social-psychological interventions in education: They're not magic. *Review of educational Research, 81*(2), 267-301.
- You, S., & Sharkey, J. (2009). Testing a developmental-ecological model of student engagement: a multilevel latent growth curve analysis. *Educational Psychology, 29*(6), 659-684.
- Zee, M., & Koomen, H. M. (2016). Teacher self-efficacy and its effects on classroom processes, student academic adjustment, and teacher well-being: A synthesis of 40 years of research. *Review of Educational research, 86*(4), 981-1015.

- Zeng, G., Hou, H., & Peng, K. (2016). Effect of Growth Mindset on School Engagement and Psychological Well-Being of Chinese Primary and Middle School Students: The Mediating Role of Resilience. *Frontiers in psychology, 7*, 1873.
- Zimmerman, B. J. (2000). Self-efficacy: An essential motive to learn. *Contemporary educational psychology, 25*(1), 82-91.
- Zuffianò, A., Alessandri, G., Gerbino, M., Kanacri, B. P. L., Di Giunta, L., Milioni, M., & Caprara, G. V. (2013). Academic achievement: The unique contribution of self-efficacy beliefs in self-regulated learning beyond intelligence, personality traits, and self-esteem. *Learning and Individual Differences, 23*, 158-162.