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Academic Motivation Profiles of 10th Grade Students: Exploring A Relationship with Socioeconomic Level Using a Person Oriented Approach

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ACADEMIC MOTIVATION PROFILES OF 10TH GRADE STUDENTS: EXPLORING A RELATIONSHIP WITH SOCIOECONOMIC LEVEL USING A PERSON ORIENTED APPROACH

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DEDICATION

This dissertation is dedicated with the deepest love to my husband, Steven Rogelberg, and to my sister, Kathy, and my father-in-law, Joel. You have all been inspirations to me during this journey, and beyond.

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ABSTRACT

Motivation is an important predictor of educational success, as is socioeconomic status. This study used Expectancy Value Theory (EVT) and a person oriented approach as the framework to explore how motivation profiles may be related to context, namely socioeconomic status (SES), and the roles these profiles have in predicting education outcomes. Five motivation variables: math self-efficacy, reading self-efficacy, control expectation, action control, and utility value (instrumentation motivation) were used in latent profile analysis to determine four latent motivation profiles from a national sample of 10,981 10^{th} grade students using ELS:2002 data. Family income and education level (SES) were considered a context. Per the EVT model, contexts may relate to the development of ability beliefs, expectancy beliefs, and values, the main constructs in this theory. SES predicted membership into motivation profiles to a statistically significant degree. Various statistical analyses converged on the same theme: SES level was related to motivation class assignment. In turn, *high* and *moderate* motivation profiles predicted favorable educational outcomes when all SES levels were analyzed together, but these outcomes were not as clear when the lowest SES level was analyzed independently. Implications of these findings is discussed.

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CHAPTER 1

INTRODUCTION

"There are three things to remember about education. The first is motivation. The second one is motivation. The third one is motivation" (Maehr & Meyer, 1997, p. 372).

For decades, the income achievement gap has been widening: The disparity between academic achievement of American K-12 students from low-income and high-income families continues to grow and children from middle-class and affluent families out-perform children from low-income families on most every educational outcome measure, including graduation rates and college enrollment (Reardon, 2011, 2013). Indeed, socioeconomic status (SES), the social standing of an individual or group measured by a combination of income, education, and occupation (APA, 2017), is a key factor in educational outcomes. Meta-analyses have shown that family income and educational level has a large effect on academic achievement (Sirin, 2005). SES has been given much attention in recent years as scholars wrestle with the issue of closing the ever-widening income-achievement gap, which has now surpassed and is more than twice as large as the Black-White achievement gap (Duncan & Murdane, 2011; Reardon, 2011, 2013).

Motivation plays another critical role in education. It predicts the amount of effort students exert in learning, how long they persist in academic tasks, and ultimately their levels of achievement (Schunk, 1991). Students who experience academic success, as measured by performance on achievement tests, high grade point averages, and graduation from high school are better poised to continue their education through college enrollment, which in turn predicts higher annual income (Davis-Kean, 2005). Some studies indicate that key motivation factors such as self-efficacy may be more predictive of future educational outcomes than previous achievement or socioeconomic status (Zuffiano, Alessandri, Gerbino, Kanacri, DiGuiunta, Milioni, & Caprara, 2013). In addition, research has established that motivation factors do not necessarily work in isolation, but rather when combined form different profiles or patterns that create favorable or less favorable outcomes (Dweck & Molden, 2005; Senko, Hulleman, & Harackiewicz, 2011). The influence of contextual variables, such as low SES, on motivation in students is unclear. Understanding motivation in students from low SES may be especially important given education may be the only path out of poverty.

1.1 THEORETICAL FRAMEWORK

The current study uses the lens of Expectancy Value Theory (EVT) and applies a person oriented approach (POA) to explore motivation profiles and to examine how they predict achievement, graduation from high school, dropout, college enrollment, and college graduation. EVT posits that if a person believes they have the ability to perform well in an activity or task, expects to perform the activity well either presently or in the future, and finds value in that activity, then that individual is likely to choose to engage in that activity (Wigfield & Eccles, 2000).

As indicated in the model, there are three primary motivation constructs of interest: ability beliefs, expectancy beliefs, and value. Ability beliefs refer to one's self-assessment about their competence at a specific task and how well they believe they compare to others at the same task (Wigfield, Tonks, & Eccles, 2004), similar to self-efficacy (Bandura, 1997). Expectancy beliefs refer to one's belief about how they will perform the task in the future based on ability beliefs (Wigfield, Tonks, & Eccles, 2004). Value is defined based on factors such as the importance of the activity (attainment value), the level of enjoyment (intrinsic value), the significance the activity holds currently or in the future (utility value), and the cost – other activities given up in order to participate in the activity of choice (Wigfield, 1994; Wigfield & Eccles, 2000; Wigfield, Tonks, & Eccles, 2004). Contextual factors such as biological, psychological, social, cultural influences, and environment are also included in the EVT model. These less studied factors in the model are important because they may be significant determinants of the more frequently studied primary constructs (Wigfield & Eccles, 2000; Wang & Degol, 2013).

1.2 PERSON ORIENTED APPROACH

A person-oriented perspective considers the individual as a whole, assumes development is based on interactions between individual and environmental factors, and is often used in research focused on individual development (Bergman & Magnusson, 1997). A person-oriented perspective rests on number of assumptions (Bergman & Magnusson, 1997; von Eye & Bogat, 2006). First, the developmental process is, in part, specific to individuals. In other words, every person's development is unique. Second, there are many components involved in the developmental process, so interactions are complex and complicated. Despite countless interactions between the numerous individual factors and environmental factors, there is a "lawfulness" in the developmental process. This lawfulness results in the emergence of different patterns of factors. While theoretically there are infinite potential combinations and patterns/groupings, these patterns tend to be distributed so that some patterns emerge more frequently than others (Bergman & Magnusson, 1997; von Eye & Bogat, 2006). Meaning is derived based on how the interactions of factors are interpreted. To meet the criteria of a person-oriented approach (POA), a term used in research studies, it is assumed that the sample is comprised of many sub-populations, that external validity of the groupings is tested/explored, and that the interpretation of the groupings is done through the lens of developmental theory (von Eye & Bogart, 2006).

POA not only requires the lens of developmental theory, as discussed above, it also requires a commensurate methodological approach (Bergman & Trost, 2006; Sterba & Bauer, 2010). Unlike variable-oriented approaches where the variables themselves are the focus of research, in research using a person-oriented perspective, it is the constellation of the variables and the patterns that emerge from them that provide a more holistic view of the individual (Bergman & Magnusson, 1997) and provide insight to the phenomenon under investigation. Statistical analyses appropriate for POA include cluster analysis, latent class analysis/latent transition analysis, and other model-based classification methods (Bergman & Magnusson, 1997).

1.3 GAP IN THE LITERATURE

Research findings from the extant literature is clear; poverty has deleterious effects on the development and academic outcomes of children (Brooks-Gunn & Duncan, 1997; Conger & Donnellan, 2007; Duncan & Brooks-Gunn, 2000; Evans, 2004; McLoyd, 1990, 1998; Sirin, 2005). The literature is less clear about the role that SES plays in academic motivation. There are only a handful of studies that use at-risk populations, such as students from low SES, to explore motivation profiles (Finn and Rock, 1997; Irvin, 2012).

The EVT model of motivation posits that personal, social, and environmental contexts, such as economic disadvantage, are involved in the development of important measures of academic motivation, such as self-efficacy, outcome expectancies, and values (Wigfield & Eccles, 2000). Research has demonstrated a relationship between SES and motivation (Bandura, Barbaranelli, Caprary, & Pastorelli, 2001; Battistich, Solomon, Kim, Watson, & Schaps, 1995; Brown, 2009; Malakoff, Underhill, & Ziegler, 1998; Stipek & Ryan, 1997; Ziegler & Kanzer, 1962), but this research is limited by its variable oriented approach. These studies focus on mean differences or explain how much a measure of a motivation factor explain outcomes, but are unable to provide information about what other factors may be operating on the individual simultaneously, that might also contribute to the outcome.

A person-oriented perspective can provide a more holistic view on an individual because it considers the interaction of multiple variables that result in patterns. This perspective may be particularly applicable to motivation studies because motivation variables have been found to combine and work together, versus operate individually, to create favorable or less favorable outcomes (Dweck & Molden, 2005; Senko, Hulleman, & Harackiewicz, 2011). Research using person-oriented approaches, such as cluster analysis and latent profile analysis, have demonstrated the usefulness of this methodology for finding motivation profiles in high school students and how profiles predict academic outcomes (Hayenga & Corpus, 2010; Ratell, Guay, Vallerand, & Senecal, 2007; Tuominen-Soini, Salmela-Aro, & Niemivirta, 2011; Viljaranta, Nurmi, Aunola, &

Salmela-Aro, 2009; Wormington, Corpus, & Anderson, 2012). These studies include measures of motivation (sometimes from different theories), as well factors, such as previous achievement, poverty risks, and demographic information, which increase our understanding of the whole person by providing profiles, which can then be used to predict outcomes in high school students. This information may be especially helpful given the high stakes decisions faced by that age group, such as entering the work-place or continuing with post-secondary education.

To date, there are no known studies that address the intersection where there is a gap in research: motivation profiles in a large, nationally representative sample of 10th grade students, using EVT motivation constructs, while also considering the role of SES as a contextual factor in the formation of these constructs. As such, this study aims to fill the gap in research by addressing the following research questions:

1. What motivation profiles are evident within a national sample of 10th grade students?
2. How does SES predict motivation class membership?
3. Which motivation profiles best predict outcomes for students at the lowest SES level?

1.4 SIGNIFICANCE OF THE STUDY

This research study aims to contribute to the literature in a number of important ways. First, this study will be the first to explore motivation profiles in a nationally representative sample of high school students during a time when motivation is vulnerable, yet perhaps most important as students are on the cusp of independence as they prepare for very consequential decisions such as pursuing post-secondary education or entering the workforce. Second, it will explore the role of SES level on the motivation class membership. Third, by exploring other contexts (e.g. demographics), this study will contribute to the existing literature that demonstrates heterogeneity in motivation profiles among those considered at-risk (low-income and minority populations), which is important in dispelling deficit model thinking about those from marginalized populations (Irvin, 2012). Lastly, while most motivation studies are cross sectional (Battle & Rotter, 1963; Brown, 2009; Friedman & Friedman, 1973; Malakoff, Underhill, & Zigler, 1998; Steinmayer & Spinath, 2009; Stipek & Ryan, 1997; & Zigler & Kanzer, 1962), this study will add to the literature by taking a longitudinal approach and exploring the impact of the motivation profiles on important outcomes, namely achievement scores, high school graduation, post-secondary education enrollment, and college graduation.

CHAPTER 2

LITERATURE REVIEW

There are numerous theories that attempt to explain what drives students to learn and succeed in school. Attribution theory (Weiner, 1979), Expectancy Value Theory (Wigfield & Eccles, 2000), Goal Theory (Ames, 1992; Dweck, 1986; Urdan & Maehr, 1995), Self-Determination Theory (Ryan & Deci, 2002), and Entity Theory (Dweck, Chiu, & Hong, 1995) are to name but a few. Although there are differences in conceptualization, common constructs are often found among them. This chapter provides a more in-depth review of the literature in a number of areas. First, this chapter will use the lens of Expectancy Value Theory (EVT) to explain what motivates students. This theory was selected over others because it includes a number of the constructs that are identified in the field as being important to academic success. Additionally, the EVT model offers biological, psychological, social, and cultural components, which are less studied, yet help explain how different contexts are involved in the formation of these primary constructs. As such, research is presented that looks at the context of economic disadvantage and findings as it relates to motivation followed by a review of the literature of five motivation constructs as they relate to academic outcomes. Next, a person-orientated approach is introduced, followed by research findings about the contributions of this type of analysis. Gaps in research are then presented, which lay the groundwork for the rationale for this study. Finally, the aims of this study are delineated.

2.1 EXPECTANCY VALUE THEORY OF MOTIVATION

Expectancy Value Theory (EVT) posits that if a person believes they have the ability to perform well in an activity or task, expects to perform the activity well either presently or in the future, and finds value in that activity, then that individual is likely to choose to engage in that activity (Wigfield & Eccles, 2000). The EVT framework might be expanded from a specific task and applied more broadly to education in general, for example, at the high school level. It might translate like this: If an individual believes they have the ability to perform well in high school, expects to perform well in their current and future classes, and finds value (e.g. enjoys learning or feels doing well in high school will improve their chances of getting into college or securing a job), then the individual will likely engage in behaviors (such as completing homework, participating in class) that will result in doing well academically and influence their choices to pursue post-secondary education.

As indicated in the model, there are three primary motivation constructs of interest: ability beliefs, expectancy beliefs, and value. Ability beliefs refer to one's self-assessment about their competence at a specific task and how well they believe they compare to others at the same task (Wigfield, Tonks, & Eccles, 2004), analogous to self-efficacy (Bandura, 1997). Expectancy beliefs refer to one's belief about how they will perform the task in the future based on ability beliefs (Wigfield, Tonks, & Eccles, 2004). Value is defined based on factors such as the importance of the activity (attainment value), the level of enjoyment (intrinsic value), the significance the activity holds currently or in the future (utility value), and cost – other activities given up in order to participate in the activity of choice (Wigfield, 1994; Wigfield & Eccles, 2000; Wigfield, Tonks, & Eccles, 2004).

Also included in the EVT model are contextual factors that potentially influence these motivation constructs, such as biological, social, and cultural influences (Wigfield & Eccles, 2000). Cultural influences include perceptions about gender roles and stereotypes as well as stereotypes about occupations. Beliefs held by people who influence the individual's life, previous experiences, aptitudes, the person's self-conception, physical and mental conditions, memories, and personal goals all likely impact ability beliefs, expectancy beliefs, and values (Wigfield & Eccles, 2000; Wang & Degol, 2013).

EVT has been widely studied in the field of education. In her seminal work, Eccles and colleagues (1983) found gender differences in ability beliefs in mathematics and subsequent choice about taking math classes. These findings have been replicated in other studies (Wigfield & Eccles, 2000; Wigfield, Tonks, & Eccles, 2004) which have contributed substantially to understanding the science, technology, engineering and mathematics (STEM) pipeline. Consistently, studies have found that ability and expectancy beliefs predict achievement (Bandura, 1997; Eccles et al., 1983; Pajares & Miller, 1994). Value, however, is the better predictor of task engagement (Wigfield, Tonks, & Klauda, 2009) – the activities in which individuals choose to engage. Value of subject-matter was better at predicting enrollment in math classes (Lutrell, Callen, Allen, Wood, Deeds, & Richard, 2010; Meece, Wigfield, & Eccles, 1990), taking more advanced courses in science (Simpkins, Davis-Kean, & Eccles, 2006), English classes (Durik, Vida, & Eccles, 2006), choice of college majors (Hackett & Betz, 1989), and career choices (Lent, Lopez, & Bieschke, 1991). These findings have extended to studies outside the STEM area. When EVT constructs were applied to sports, the findings were consistent: value in sports-related activities predicted choice in physical activities (Cox & Whaley, 2004; Gao, 2008; Guan, Xiange, McBride, & Bruene, 2006).

Some studies have explored how some of the less studied contextual factors in the EVT model (e.g. biological, social, and cultural factors), operate on values and subsequent career choices. Societal and cultural factors were found to predict that women were more likely to pursue occupations that require social interaction (Fredricks & Eccles, 2005; Ruble & Martin, 1998; Su, Rounds, & Armstrong, 2009), while men were encouraged to pursue careers in the STEM fields (Benbow et al, 2000; Lubinski, Webb, Morelock, & Benbow, 2001) and high-paying jobs (Watt, Eccles, & Durick, 2006).

Wang and Degol (2013) reviewed the literature and took a theoretical perspective on how ecological factors influenced student motivation related to STEM fields. Specifically, they deconstructed how school and classroom factors (e.g., teacher expectations, student treatment, stereotypes, teaching practices, etc.) impacted motivation to pursue additional education in the STEM fields. While their interest was in how these various factors influenced motivation in STEM, the principles can be extrapolated to illustrate how poverty and disadvantage could feasibly operate in ecological contexts that might also influence student motivation.

The literature has clearly established that schools in economically disadvantaged neighborhoods that serve students at lower socio-economic levels are qualitatively different than more economically advantaged students (Kozol, 2005; Reardon, 2013).

Students attending schools in neighborhoods with high concentrations of disadvantage are exposed to more violence and have the lowest achievement scores (Burdic-Will, Ludwig, Raudensbush, Sampson, Sanboumastu, & Sharkey, 2012). Students who attend schools serving predominantly low SES communities or "poor schools" are more likely to be "tracked" in vocational versus college-prep curriculum (Maaz, Trautwein, Ludtke, & Baumert, 2008; Oakes, 1990), and are less college ready than their more affluent peers (Tierny, 2015). Additionally, poor schools have classrooms where there are more behavior problems (Farkas, 2011), have less qualified and less experienced teachers (Lee, Smith, & Croninger, 1997; Isenberg, Max, Gleason, Johnson, Deutsch, & Hansen, 2016), and have teachers who hold lower expectations of their students (Rist, 2000; Rosentlutl & Jacobson, 2000). All of these factors undoubtedly weigh on motivation formation, similar to how factors operate on values formation. Over the course of a child's development, the interactions of contextual factors will result in different outcomes on a number of motivation factors, which would in turn, impact academic outcomes.

2.2 RESEARCH ON SOCIOECONOMIC STATUS AND MOTIVATION

Poverty is an important contextual factor that impacts child development and educational outcomes. The income-achievement gap of American K-12 students continues to grow and children from middle-class and affluent families out-perform children from low-income families on most every educational outcome measure including graduation rates, college enrollment, and college completion (Reardon, 2011, 2013). Indeed, family income is one of the most powerful predictors of intellectual functioning and behavioral problems (Duncan, Brooks-Gunn, & Klebanov, 1994; McLoyd, 1990, 1998). Economic deficiencies translate to lower achievement scores, lower graduation rates, and lower rates of enrollment in post-secondary education (Duncan & Magnuson, 2011; Farcas, 2011).

Research has examined motivation variables as they relate to race/ethnic differences to better understand lower levels of achievement, higher dropout rates, and lower rates of college enrollment in African American and Hispanic populations compared to the White population. Motivation variables (self-efficacy, attainment value, utility value, intrinsic value) differentially predicted persistence in STEM coursework in high school students depending on race/ethnicity (Andersen & Ward, 2013). Achievement goals, on the other hand predicted achievement in Hispanic students entering high school (Wilkins & Kuperminc, 2009), math achievement in African American students transitioning to high school (Gutman, 2006), and reading achievement in African American and White students (Gutman, 2006; Guthrie, Coddington, & Wigfield, 2009). Another motivation factor, self-efficacy, operated differently on Hispanic students than it did with a heterogeneous population (Stevens, Olivarez, & Hammon, 2006), and Eccles, Wong, and Peck (2006) found that when at risk for racial discrimination, students' academic performance (i.e. GPA) in addition to overall motivation declined in some, but improved motivation for others, especially those with a strong ethnic identity. None of these studies parsed out income or SES specifically, so the interplay of race/ethnicity and socioeconomic status and how these contextual variables operate on motivations remains murky.

Pioneering educational research in the 1960s and 70s began to look at how economic status, a broad contextual factor, affected children's motivation. Ziegler and Kanzer (1962) found that praise feedback ("good") was more effective in increasing performance for low SES elementary aged children, while correction feedback ("correct") was more effective with middle SES children. Additionally, students from middle-SES received statistically significant more reinforcement than low-SES students (Friedman & Friedman, 1973). Battle and Rotter (1963) found that "lower class" African American students made more external attributions than middle-class African American or White students, and "middle-class" children made more internal attributions than did "lower class" students. Additionally, African American students from the "lower class" with high IQs rated higher on external control than middle class Caucasian children with lower IQs (Battle & Rotter, 1963). Today these studies would be heavily scrutinized for their small sample sizes and pejorative language that could be interpreted as evidence of institutional racism, but their findings speak to how classroom, economic, and societal factors could be internalized by children and thus impact motivation.

Research spanning decades has continued to reveal similar findings. Malakoff, Underhill, and Ziegler (1998) found mastery motivation, level of challenge, and persistence significantly higher in middle SES children than children from low SES, with low SES children enrolled in Head Start having higher levels of motivation than their peers who were not enrolled in preschool. Brown (2009) also found that younger children, those with more risks for poverty, those who had more attention problems, and those children who held emergent entity beliefs about intelligence were less likely to persist on a challenging academic task. Finally, Battistich and colleagues (1995) used hierarchical linear modeling to explore more complex relationships between contextual variables at the student level and school level. They found that poverty negatively related to most all student outcomes including academic motivation (preference for challenging tasks, intrinsic motivation), achievement, and social functioning.

These findings were consistent with the burgeoning literature of the 1990's connecting economic disadvantage to less favorable outcomes related to development (Brody, Stoneman, & Flor, 1995; Brody, Stoneman, Flor, McCrary, Hastings, & Conyers, 1994; Conger, Conger, Elder, Lorenz, Simons, & Whiteback, 1992; and McLloyd,1990), intellectual abilities (Duncan, Brooks-Gunn, & Kebanov, 1994), physical health, cognitive development, academic achievement, and internalizing and externalizing problems (Brooks-Gunn & Duncan, 1997; McLloyd, 1998).

There are studies, however, that refute these findings and suggest that motivation is robust even in the face of adversity. Stipek and Ryan (1997) found that preschool and kindergarten children from higher SES had statically higher scores on academic related measures (e.g., basic reading and math skills) than their less affluent peers, but when it came to measures of motivation, such as perceptions about competencies, attitude toward school and willingness to take on learning challenges, there were almost no differences between children from different economic levels. Interestingly, the researchers found that children from higher SES were more likely to feel anxious about their performance and were more dependent on teachers than their less economically advantaged peers (Stipeck & Ryan, 1997). And while poverty tended to have negative consequences on many academic outcomes, Battistch and colleagues (1995) also found that having a high sense of community related to their school ameliorated these effects, especially for those from the poorest schools (Battistch et al., 1995). Although causal relationships cannot be determined from this study, the findings suggest that poverty negatively impacts motivation, but there is hope that such effects can be offset by other contextual variables, such as caring teachers and feeling part of a caring community, which may bolster motivation.

All of the aforementioned studies about motivation differences focused on children. Only one study was found that addressed the operation of contextual variables on motivation in adolescence. Bandura, Barbaranelli, Caprary, and Pastorelli (2001) tested a model to determine the socio-cognitive influences that govern children's occupational self-efficacy that goes into making career choices. Path analyses found that SES had no direct effect on children's self-efficacy, academic aspirations and achievement, occupational efficacy, or occupational choices, but rather an indirect effect through parent's parental perceived academic efficacy and educational aspirations. Parents from upper income brackets had stronger beliefs in their ability to further their children's academic development and held higher aspirations for their children's educational and occupational aspirations. This in turn influenced their children's efficacy for academics, social situations, and self-regulation (Bandura et al., 2001). This study was conducted in Italy when students were at the end of middle school, a pivotal time in their educational process when they must choose one of seventeen different educational tracks to pursue, ranging from vocational to professional. While the educational system in Italy is quite different from that in the United States, this study highlights the importance of understanding the motivation mindset of students at key junctures of students' lives.

Indeed, in the United States, high school may be the most important period of time to explore student motivation. Developmentally, adolescence marks a time when academic motivation decreases (Eccles & Midgley, 1989; Eccles & Roeser, 2009). This decline in motivation may be reflected in the number of students who do not graduate from high school. According to Chapmans, Laird, Ifill, Kewal-Ramani (2011), approximately 3.4 percent of 10^{th} through 12^{th} grade high school students dropped out of high school during the 2008-2009 academic year, down from 6.1 percent in the 1972. Lack of academic and learning engagement, which correlates with motivation (Goodenow & Grady, 1993) and student achievement are primary factors in students' decision to drop out of school (Rumberger, 2001). Socioeconomic status, in addition to being predictive of intellectual development and behavioral problems (Duncan, Brooks-Gunn & Klebanov, 1994; McLoyd, 1990, 1998), is also one of the most powerful predictors of achievement and dropout (Pong & Ju, 2000; Rumberger, 2001). In 2009, students from low-income families had a dropout rate of approximately five times greater than high-income families, 7.4 % compared to 1.4 % (Chapmans et al., 2011). Quite ironically, adolescence is also the time when youth are faced with weighty decisions that have far-reaching consequence on their futures, such as whether to pursue post-secondary education or enter the work-force, thus increasing the need to better understand the role of motivation in this population. Understanding academic motivation and factors that encourage students to succeed academically is critical, particularly for students coming from disadvantage as academic success may be one of the only viable path out of poverty.

To summarize, early research, many of which looked at young children, found differences between motivation measures in student from different socioeconomic levels using simple mean testing (Battle & Rotter, 1963; Friedman & Friedman, 1973;

Malakoff, Underhill, & Zigler, 1998; Ziegler & Kanzer, 1962). While Brown's (2009) study also suggested that SES may negatively relate to motivation (persistence), the statically significant 23% variance that explained perseverance issues in low SES children included many risk predictors, behavior scores, and did not parse out SES, thus making the picture a little less clear. Findings from a studies by Battistich et al. (1995), Stipek and Ryan (1997), and Bandura and colleagues (2001) confound these finding and call into question if, or to what degree, SES operates directly or indirectly on motivation. The next section addresses research on five motivation constructs: math self-efficacy, English self-efficacy, expectancy beliefs, instrumentation, and action control especially as they relate to high school students, keeping contextual factors such as socio-economic status in mind.

2.3 RESEARCH ON MOTIVATION CONSTRUCTS

Research on the role of self-efficacy on educational outcomes. Self-efficacy is an individual's belief in their ability to perform a specific task, which in turn affects behavioral choices, effort, and persistence (Bandura, 1977; Zimmerman, 2000). Beliefs about one's abilities to perform tasks can result in avoidance of tasks, weak commitment, and negative affect (such as anxiety and self-doubt), or high level of engagement, interest, commitment to a goal, and persistence (Bandura, 1993). Self-efficacy is built through four sources: 1) enactive mastery, or recognition of previous success; 2) vicarious experiences, observing a person with relatable characteristics succeed at a task; 3) verbal persuasion and encouragement; and 4) increased awareness and management of affective states (Bandura, 1977, 1993; Margolis & McCabe, 2006). Self-efficacy holds a particularly important role in academic motivation because it positively relates to so many academic outcomes, namely achievement, skills, previous experiences, goal-setting, information processing, application of learning strategies in the classroom context where students may have less choice about what they want to learn (Pajares & Schunk, 2001; Schunk, 1991), and because it has been shown to predict students' choices in activities, amount of effort, and persistence (Zimmerman, 2000). Moreover, domain specific self-assessments, beliefs about abilities in specific subjects, were found to be even stronger in predicting grades than intelligence (Steinmayr & Spinath, 2009). Virtually all K-12 curricula focus on math and literacy skills. Studying self-efficacy in these domains is important because proficiency in both of these areas predicts socio-economic status in adulthood (Ritchie & Bates, 2013). Indeed, low literacy predicts incarceration, which is most likely to plague individuals of low socioeconomic status (Christle & Yell, 2008).

Following the introduction of the self-efficacy construct in 1977, there was a spate of research which culminated in a meta-analysis of 39 articles that examined the effects of self-efficacy on performance and persistence in school (Multon, Brown, & Lent, 1991). The study concluded that self-efficacy was not just a robust predictor of academic performance and persistence, but it demonstrated that self-efficacy in combination with other variables could have a synergetic effect on outcomes (Mutlon et al., 1991). This meta-analysis made an early contribution to the literature by highlighting the positive effect of this important motivation construct on academic success. Additionally, it set the table for future studies to explore the role of self-efficacy as a moderator and mediator. However, one of its limitations was there was no attention given to any relationship between self-efficacy and socio-economic status, or other demographic information.

On-going research has consistently found that self-efficacy is not only an important predictor for achievement, but it also predicts university enrollment and choice of college major (Betz & Hackett, 1983; Hackett, 1985). More recently, Parker, Marsh, Ciarrochi, Marshall, & Abduljabbar (2014) found that while both self-efficacy and self-concept predicted achievement in subject matter (math, science, and reading), self-efficacy was a stronger predictor of tertiary entrance rank (criteria for admission into college in Australia) over self-concept, and when covariates were entered, self-efficacy explained more than 50% ($R^2 = .57$) of the variance for university enrollment (Parker et al., 2014).

Research in math self-efficacy. As previously stated, domain-specific self-efficacy is important to educational outcomes. Self-efficacy in math not only predicts performance, but also choice to take more math courses in high school (Steinmayr & Spinath, 2009). Math level at 10th grade and the subsequent choice in the sequence of higher level math classes set an educational trajectory that not only affects graduation, but whether a student enrolls in college, and college graduation (Schneider, Swanson, & Riegle-Crumb, 1998). Betz & Hackett (1983) investigated the relationship between math self-efficacy and the selection of science-based college majors and found self-efficacy explained 36% of the variance in choice of science based college majors (Betz & Hackett, 1983). Early research by Pajares & Miller (1994) used path analysis and found self-efficacy in solving math problems had a significantly stronger effect on math performance than math self-concept. This study used college students, but years later similar findings were replicated in a study in Australian high school students through more complex analyses, such as structural equation modeling (Pietsch, Walker, & Chapman, 2003) and hierarchical regression and relative weights analysis (Steinmayr & Spinath, 2009). Hackett (1985) found that, in addition to gender, other variables such as socio-economic factors and socio-cultural influences may also impact self-efficacy in math. Math self-efficacy was shown to be robust regardless of socio-economic status. The study by Pietsch and colleagues (2003) used a sample of 416 students, all from low socio-economic status, and most (80%) of whom were not native English speakers. By contrast, Steinbayr's & Spinath's (2009) sample was comprised of primarily White, German high school students in a college-track school (Gymnasium).

Research on English self-efficacy. Proficiency in English includes skills in speaking, writing, listening, and reading, and are categorized into five levels: distinguished, superior, advanced, intermediate, and novice (American Council on the Teaching of Foreign Languages, 2012). Reading and writing skills are typically measured at each grade through standardized test scores as well as grades. Writing skills are particularly important in the workplace, not just to for purposes of clear communication, but to convey professionalism, credibility, and are consideration factors for job advancement (Career Addict, 2016).

Shell, Murphy, and Bruning (1989) found that self-efficacy in reading skills and writing skills independently accounted for performance on a reading test and an essay. In addition, there was a statistically significant Canonical correlation for the combined self-efficacy and expectancy beliefs on performance, which supported their hypothesis that reading and writing skills are highly related to each other (Shell et al., 1989). Pajares &

Johnson (1996) found that self-efficacy in writing was also the strongest predictor of performance in native English speaking high school students. A particularly important finding in this study was that Hispanic students had statistically lower scores on self-efficacy, aptitude, and performance, and higher apprehension than their non-Hispanic peers, even though these students were considered native English speakers (Pajares & Johnson, 1996). This finding seems especially poignant given the rising population of Hispanic and other English language learners in today's classrooms.

In summary, the findings about self-efficacy, whether in math or literacy skills, support that self-efficacy belief was one of the strongest predictors of academic outcomes. Without exception, all of these studies used some form of regression analysis which showed that when combined with other motivation factors, such as self-concept, more variance was explained, and there seemed to be a synergetic effect between self-efficacy and other variables, a notion that was suggested by Multon, Brown, & Lent (1991) in their meta-analysis. Other methods, other than variable-oriented approaches, were not utilized in any of the aforementioned studies, but might add light to how motivation factors work together.

Research on expectancy beliefs on educational outcomes. Outcome expectancy is defined as "the person's estimate that a given behavior will lead to certain outcomes" (Bandura, 1977, p. 193). In other words, it is the belief that a behavior (or set of behaviors) will impact a certain outcome. For example, the belief that doing well in school will lead to a good paying job. This construct has nuanced differences with efficacy beliefs. While expectancy beliefs are about behaviors that lead to an outcome (i.e. doing well in school), self-efficacy is about a person's belief about their ability to *enact* the behaviors (e.g. effort and persistence) that impact outcome expectancies (Bandura, 1977).

The nuanced difference between efficacy beliefs and expectancy beliefs has been somewhat controversial. Some studies have parsed out the effect of each construct on performance (Maddux, Sherer, & Rogers, 1982; Shell et al., 1989), but factor analyses found that self-efficacy and outcome expectancy beliefs loaded on the same factor and were indistinguishable (Eccles et al., 1993; Eccles and Wigfield, 1995), thus confounding the role that outcome expectancy plays in academic achievement.

None-the-less, the relationship between expectancy beliefs and academic achievement has been studied with sufficient intensity to merit two meta-analyses. Findley and Cooper's (1983) meta-analysis used 75 studies published in the 1970's and concluded control expectancies had a positive effect on academic achievement, especially in elementary and high school students when compared to other grade levels, suggesting that expectancy beliefs may operate differently depending on the population. Kalechstein & Norwicki (1997) sought to replicate findings from Findley and Cooper's (1983) study but added a component of Rotter's social learning theory using articles published between 1983 and 1994. Their hypothesis that generalized control expectancies was a better predictor than domain-specific expectancy beliefs was not supported, but Findley and Cooper's (1983) findings were replicated; expectancy beliefs operated differently depending on education level. Additionally, they recommended further exploration of moderating variables, such as race and SES, to deepen our understanding of the relationship between control-expectancy and academic achievement beyond the typically studied Euro-American participants.

Indeed, findings from a study by Shell, Colvin, & Bruning (1995) suggested that outcome expectancy beliefs may play an important role in motivation, and eventually achievement outcomes, especially for students who perform on the lower end of the achievement spectrum. Interestingly, self-efficacy beliefs, outcome expectancy beliefs, and causal attributions were quite different depending on level of achievement. Students who had high reading and writing achievement scores had high-self efficacy, believed their success was due to intelligence and effort (internal causal attributions), as opposed to luck (external attribution), yet scored low on measures of outcome expectancies, indicating they did not believe that their behavior would result in a particular outcome, which contradicted previous research findings. Conversely, students who scored low on the reading and writing achievement test, had low self-efficacy for reading and writing, tended to make external attributions, yet had high beliefs about outcome expectancies, suggesting that they believed certain behaviors were important for high achievement, but did not feel they had they ability to enact these behaviors. For lower achieving students, outcome expectancies were more important, and therefore an important factor in motivation demanding both emphasis as well as instructional strategies to help students enact achievement (Shell et al, 1995). The robustness of the outcome expectancy belief construct as a stand-alone measure is not clear, yet may offer an added dimension to understanding motivation and outcomes.

Research on action control. Action control is a less well-defined construct. Kuhl (1984) conceived of "action control" in relation to predicting human behavior, which questioned how people attempted to perform an intended action in spite of competing external and internal forces that could result in alternative actions, and thus different outcomes. Skinner, Chapman, & Baltes (1988) conceptualized "perceived control in an action" as how people viewed what is responsible for outcomes, the role they played in events leading to outcomes, and the resources people used to reach their goals. Literature in the area of high school engagement has also contributed to our understanding how both individual student characteristics and school-related variables result in either successful completion or dropout (Jimerson, Campos, & Greif, 2003). Although there is variability in definition and how this construct is measured, these all converge on one common aspect of the definition: action control requires personal agency that translates into time, effort and persistence in academic tasks, all of which contribute to academic outcomes. The review of the literature for this construct will be based on research that uses measures of effort, time, and persistence to define action control.

Research supports that action control plays an important role in educational outcomes at all grade levels. Effort was found to be the best strategy for attaining good grades and the easiest to enact, followed by beliefs about ability, the influence of powerful others, with luck being unimportant to contributing to grades (Skinner, Wellborn, & Connell, 1990). Stewart (2007) found a positive correlation between school commitment (as measured by effort, value, and satisfaction) and students' positive feelings about the school (school attachment) in 10^{th} grade African American students. In a follow up study, Stewart (2008) found that school commitment was the best predictor of GPA, but contextual factors, such as school poverty, proportion of non-White students, urbanicity, and social problems were not related to GPA.

Other research findings suggested that contextual factors may effect beliefs about action control. The belief in the power of effort may be dependent on country of origin as Americans believed effort was most important to school performance, compared to the other countries, while German students felt ability was most important (Little, Oettingen, Stetsenko, & Baltes, 1995). Ethnicity was also found to be a factor in beliefs about one's agency and effort as white students had significantly higher agency beliefs, control expectancy beliefs, performance approach goals than their non-white peers, which could have implications related to stereotype threat (Lopez, 1999). Additional studies are needed to explore how other factors, such as poverty, neighborhood, family constellation, or societal factors affect students' beliefs about their abilities to impact their own achievement in school.

Research on instrumentation motivation. The terms instrumentation motivation and integrative motivation are terms rooted in second language learning (Gardner & Lambert, 1972). Instrumentation motivation is defined as the desire to learn because it will have a positive utilitarian outcome, such as employment or job advancement, while integrative motivation is the desire to learn in order to better assimilate into a desired group (Gardner & Lambert, 1972). These definitions have significant over-lap with extrinsic motivation, engaging in an activity because it will lead to a desired outcome, and intrinsic motivation, engaging in an activity for its own sake, as defined by Pintrich and Schunk (2002). These concepts are reflected in a number of motivation theories. For example, Self-Determination Theory (Ryan & Deci, 2002) used the terms intrinsic and extrinsic motivation, and Expectancy Value Theory (Wigfiled &

Eccles, 2000) as reflected in the terms "intrinsic value," the enjoyment of the activity for its own sake, and "utility value," the usefulness of the task currently or in the future.

These concepts are not mutually exclusive. Individuals may hold both types of motivations simultaneously. Individuals who measure high on instrumentation motivation/utility value may be driven to attain more practical outcomes, such as a status, material gain, or income potential, while individuals who score high on measures of intrinsic motivation/value may be motivated to meet an internal need for personal satisfaction, or driven by the desire to learn or participate in the activity for the love of it.

Instrumentation motivation contributes to academic outcomes. The terms instrumentation motivation and utility value are synonymous and are used interchangeably. Research has found that both intrinsic and utility motivation predicted grades and intentions to pursue coursework (Bong, 2001), as well in intensions to persist in (or drop out of) high school (Hardré & Reeve, 2003). While intrinsic motivation was the better predictor of intension to pursue graduate education, utility value was also a statistically significant contributor (Battle & Wigfield, 2003). These studies, however, used either predominantly White (Hardre & Reeve, 2003), or all female students seeking considering post-graduate education (Battle & Wigfield, 2003) from an elite institution (Bong, 2001) and may suggest that instrumentation motivation and intrinsic motivations may operate differently depending on race/ethnicity and gender.

Duffy and Sedlacek (2007) found that men espoused utility values (e.g. anticipated earnings, career advancement) to a statistically significant degree more than women, who tended to favor social values. Students who came from middle socio-economic status and were White were more likely to endorse intrinsic values, while students from lower and higher socio-economic levels, African American and Asian were more likely to endorse extrinsic values (Duffy & Sedlacek, 2007). This finding may speak to the notion that external factors, such as higher paying jobs, may be a motivating factors to get out of poverty.

Motivation to learn certain subjects may be necessary, and may have inherent benefits regardless of the student's interest or internal motivations. For example, learning English is necessary for practical reasons for immigrant students to navigate school, make friends, even act as translators for their parents, and gain employment to help the family financially. The academic success of these students may also be the foundation for economic stability and prosperity for generations to come. For these reasons, instrumentation motivation (utility value) may be especially important for English language learners.

The reasons to learn a second language are often very practical: to address needs like understanding others to get basic needs met, understanding concepts in school, making friends, travel, or necessary for one's career (Belmechri & Hummel, 1998), all of which are considered instrumentation motivation. Csizer and Dornyei (2005) took a very different approach to explore motivation to learn a second language by using cluster analysis and explored how five motivation variables combined to form four distinct motivation profiles. The *most motivated students* group scored highest on all the variables and had the highest scores in the area of instrumentation motivation. The study did not explore how the different profiles predicted educational outcomes, such as course grade, rather, it explored the combined effects and interferences of the different profiles related to *other selves* and learning more than one language simultaneously (Csizer & Dornyei, 2005). The value of this study would have been increased by exploring how class membership predicted more distal outcomes, such as graduation, college enrollment, or employment.

While Csizer's and Dornyei's (2005) study did not explore educational outcomes per se, the value in this study was in its methodology as it used a person oriented perspective to explore how constellation of variables worked together versus using a variable oriented approach seen in studies that test mean differences or use correlational or regression analyses. In more recent years, a person oriented approach has been gaining favor in research, and has been useful in predicting educational outcomes.

2.4 PERSON ORIENTED APPROACH

An integrative theory of human development posits that interaction between an individual's biology, psychology and behaviors with the environment shape a person's life (Ford & Lerner, 1992) and has allowed researchers to apply such concepts to studies of motivation. Integrative theory allows for the notion that individuals simultaneously hold more than one type of motivation, and that these motivations can operate together and result in different outcomes. This concept is central to the person-oriented perspective.

A person-oriented perspective is often used in research interested in individual development that considers the person as a whole, and assumes development is based on interactions between individual and environmental factors (Bergman & Magnusson, 1997). Because the person-oriented perspective posits that individual development is a process that occurs over time, a snapshot of the whole person at the specific time and space along the developmental continuum is taken at the time variables are measured (Bergman & Magnusson, 1997).

There are a number of theoretical underpinnings on which a person-oriented perspective is based (Bergman & Magnusson, 1997; von Eye & Bogat, 2006). First, the developmental process is, in part, specific to an individual. In other words, every person's development is unique. Second, there are many components involved in the developmental process, so interactions are complex and complicated. Despite these complexities, there is a "lawfulness" about how development unfolds that allows for both consistencies in individual development, while also allowing for individual differences. This lawfulness results in the emergence of different patterns of factors. While theoretically there are infinite potential combinations and patterns/groupings, these patterns tend to be distributed so that some patterns emerge more frequently than others (Bergman & Magnusson, 1997; von Eye & Bogat, 2006). Meaning about each pattern is derived based on how the interactions of factors are interpreted. To meet the criteria of a person-oriented approach (POA), a term used in research studies, it is assumed that the population includes subpopulations, that external validity of the groupings is tested/explored, and that the interpretation of the groupings is done through the lens of developmental theory (von Eye & Bogart, 2006).

POA not only requires the lens of developmental theory, as discussed above, it also requires a commensurate methodological approach (Bergman & Trost, 2006; Sterba & Bauer, 2010). Unlike variable-oriented approaches where the variables themselves are the focus of research, in research using a person-oriented perspective, the point of interest is the constellation of the variables and the patterns that emerge from them that provide a more holistic view of the individual (Bergman & Magnusson, 1997) and provide insight to the phenomenon under investigation. Statistical analyses appropriate for POA include cluster analysis, latent class analysis, latent transition analysis, and other model-based classification methods (Bergman & Magnusson, 1997).

Research using person oriented approach. One of the powerful ways POA is used in research is to demonstrate how constellations of variables manifest in different classes/profiles, which can then be used to predict outcomes. For example, Viljaranta, Nurmi, Aunola, and Salmela-Aro (2009) used POA to show how class membership predicted vocational paths in European students, where students are faced with important decisions and must choose different educational paths (e.g. vocational, college, etc.) after they complete their "compulsory" education in middle school and upon entering high school. Other studies have used class membership to predict achievement and adaptability in students from disadvantage (Conley, 2012), grade point average (Wormington, Corpus, & Anderson, 2012), dropout (Ratelle, Guay, Vallerand, & Senecal, 2007), and test how profiles change over the course of an academic year to produce different student outcomes (Hayenga & Corpus, 2010).

Pastor, Barron, Miller, and Davis (2007) demonstrated the benefits of POA over variable oriented analysis in a study comparing various approaches: multiple regression, with two person-oriented analyses, cluster analyses, and latent profile analysis to demonstrate the superiority of one approach in particular, latent profile analysis. This study was important on two levels. First, it was consistent with findings from other articles cited by showing how latent variables emerged into different profiles from a mixed population, and that these profiles predicted outcomes that were consistent with theory. Second, Pastor and colleagues demonstrated how latent profile analysis (LPA) allowed for more rigorous criteria to determine final cluster solutions, showed membership as a proportion, and verified clusters by using another sample.

Another benefit to a person oriented approach is that the profiles that emerge can illustrate the similarities and differences between groups, and perhaps more importantly, how there are similarities in populations that appear to be divergent, such as at risk populations, underscore the humanity in the variables that transcends the variables themselves (Irvin, 2012). There are only a few studies that use a person oriented approach that actually use samples that are completely comprised of a population of the same income, or otherwise considered at risk (Finn & Rock, 1997; Irvin, 2012).

There are a number of gaps in the research. No known studies examine motivation profiles in a large, nationally representative sample of 10th grade students, using EVT motivation constructs, while also considering the role of SES as a contextual factor in the formation of these constructs.

2.5 RESEARCH QUESTIONS

As such, this study aims to fill the void in research by addressing the following research questions:

1. What motivation profiles are evident within a national sample of 10th grade students?
2. How does SES predict motivation class membership?
3. Which motivation profiles best predict outcomes for students at the lowest SES level?

CHAPTER 3

METHOD

3.1 DATA

For the current study, the Education Longitudinal Study (ELS) of 2002 data were used (ELS:2002). The overarching aim of the ELS longitudinal study was to collect data about educational access, persistence, and educational trajectories from a national sample of students beginning in their sophomore year (10th grade) of high school and follow them at two year intervals through high school (12th grade), then into post-secondary education, and/or the workplace (Ingels et al., 2014). Follow-up data were collected in 2004 (F1) when most students were in their senior year of high school (12th grade), 2006 (F2) two years after high school graduation when many were in college/postsecondary education, and 2012 (F3) eight years following high school graduation, after many individuals had completed postsecondary education and were currently in the workforce (Ingels, Pratt, Alexander, Jewell, Lauff, Mattox, & Wilson, 2014).

3.2 PARTICIPANTS

In 2002, 17,591 10th grade (sophomore) students were selected from lists of sophomore high school students provided by 752 of 1,221 eligible public, private, and parochial schools across the nation that accepted the invitation to participate in the study. (See sample design section for more details.) Participating students completed surveys about their high school activities and experiences, beliefs and opinions about themselves, plans for the future, money and work, family, and non-English language use. Additional information collected included scores from math and reading achievement tests, surveys from parents, teachers, principals, and librarians, as well as school transcripts and an observation checklist of school facilities. The information collected addressed issues related to growth in math, the drop-out process, the role of family background in educational success, and educational opportunities in subgroups (e.g. English Language Learners (ELL), students with disabilities, geographic location (urbanicity), SES, and racial/ethnic groups (Ingles, Pratt, Rogers, Siegel, & Stutts, 2004, 2005; Ingels et al., 2014). The sample on which the analysis for this study is based is 10,981. (See missing data for explanation about the reduced sample size.) This large sample is ideal for studies using POA specifically because the population is heterogeneous, a basic assumption on which POA analyses are based (Muthén & Muthén, 2000; von Eye & Bogart, 2006).

ELS:2002 used a stratified, two-stage random sample design, considered a complex design (i.e. not simple random sampling). In the first stage (strata) of sample collection, types of schools (e.g. private, public, and parochial.) were selected to mirror proportions of those types of schools across the nation. Of the initial 1,221 eligible schools approached to participate in the study, 752 participated. In the second stage (strata) approximately 26 students from each of the selected schools were selected to participate, oversampling Asian and Hispanic students in order to ensure adequate representation. In order to determine the rates at which Asian and Hispanic students should be oversampled, counts were obtained from the Common Core of Data and the Private School Survey (Ingles et al., 2004).

3.3 VARIABLES

Control variables. In this study, the information on the control (also referred to as covariate or background) variables were collected during the base year (2002) and then cross-referenced with information from the first follow-up at which time any missing information was added, imputed, or cases were dropped. (For more information, see how missing data were handled in the section below.) The updated variables from the first follow-up year were used in the study because they include the updated information that was missing in the base year, and were the most complete and accurate. The variables are coded "F1" to reflect updated information which was collected in the base year. Control/covariate variables were used to determine how demographic and other information specific to the participant related to the motivation profiles. All control variables are complete. The terms control and covariate variables are used interchangeably going forward.

*Sex***.** The variable used for sex is F1SEX. This composite variable updated any missing information collected during the base-year to provide complete information on participants' sex. The sample consists of 5,145 males and 5,836 females (N = 10,981).

Race/Ethnicity. The variable used for race/ethnicity is F1RACE. This variable updated the BYRACE variable collected during the base year in 2002 and included imputed data for missing information. It is a composite of seven dichotomous variables: White, non-Hispanic (n = 7,25); more than one race, non-Hispanic (n = 491); Hispanic, race specified (n = 793); Hispanic, no race specified (n = 691); Black or African American, non-Hispanic (n = 1,230); Asian, Hawaii/Pac. Islander, non-Hispanic (n = 434), and American Indian/Alaska Native, non-Hispanic (n = 87), (N = 10,981).

Achievement Scores. Measures of students' 10th grade achievement in math (BYTXMIRR) and reading (BYTXRIRR) were collected in 2002 (Ingels et al., 2004). Content areas for math included arithmetic, algebra, geometry, data/probability, and advanced topics, and literary material, natural, and social sciences for reading. Students first took routing tests: 15 questions on math, and 14 questions on reading. Students were then assigned to groups of low, middle or high difficulty level, depending on correct answers, on which testing items for the second stage were based. The second stage of testing consisted of multiple choice and open-ended questions based on the pre-determined difficulty level, and was designed to maximize accuracy of the achievement scores. Scores were based on item-response theory (IRT) that accounts for items answered correctly, incorrectly, items guessed and omissions, and allows cross comparison of different levels of test difficulty. These variables are the estimated number of questions answered correctly had all 85 math questions and 51 reading questions been responded to by participating students. The IRT method is advantageous over using raw scores because it uses a pattern of correct answers and compensates for guessing hard items correctly (Ingels et al., 2004).

School urbanacity (BYURBAN). School urbanicity (geographic location of the school: urban, suburban, or rural) is based on Common Core of Data (CCD 1999-2000), Private School Survey (PSS 1999-2000), and data from student files (ELS:2002 Sampling Data). Urban schools were defined as schools in a large or mid-sized central city, suburban schools were either on the fringe of a large city, or in a large town, and rural schools were inside or outside a metropolitan statistical area (Ingles et al., 2004). The students in the sample are as follows: urban = 2,960; suburban = 5,815; and rural = 2,206 (*N*=10,981).

Socioeconomic status (SES). The SES variable (F1SES2QU) is a composite score based on family income, mother's education, father's education, mother's occupation, father's occupation broken down by quartile. Most of this information was collected during the base year from the parent questionnaire, but missing details were added after the first follow-up (thus coded F1). The information was imputed using sequential hot deck imputation, with sampling weights, if it was missing. The SES variable is based on the more recent occupational prestige ratings from the Duncan Occupational Prestige Scores updated in 1989 and therefore more current than the F1SES1QU variable on which the rating was based on 1969 version the Duncan Occupational Prestige Score. The breakdown of socioeconomic status by quartiles is as follows: lowest quartile, n = 2,435; second quartile, n = 2,709; third quartile, n = 2,883; highest quartile, n = 2,950; survey (total N = 10,977). These quartiles are based on weighted distribution (Ingels, Pratt, Wilson, Burns, Currivan, Rogers, & Hubbard-Bednasz, 2007).

Motivation variables. All the motivation variables are composite scores from sub-questions (a. through v.) on item number 89 of the base year student questionnaire. Participants responded using the following four-point scale: 1 = *almost never*, 2 = *sometimes*, 3 = *often*, 4 = *almost always*. Higher scores reflect higher motivation. The variables were created by the ELS:2002 through principal factor analysis. Only respondents who answered all items were assigned composite scores. Motivation scores were standardized as Z scores with a mean of 0, and a standard deviation of 1 (Ingels et al., 2005).

Control expectation (BYCONEXP). This variable captured student's expectations for success in academic learning in the base year. Four items were used to measure this construct: "When I sit myself down to learn something really hard, I can learn it"; "If I decide not to get any bad grades, I can really do it"; "If I decide not to get any problems wrong, I can really do it"; and "If I want to learn something well, I can." Internal consistency reliability (α) was 0.84.

Action control (BYACTCTL). Action control was student's self-rated effort and persistence in the base year measured by the following four items: "When I study, I make sure that I remember the most important things"; "When studying, I try to work as hard as possible"; "When studying, I keep working even if the material is difficult"; and "When studying, I try to do my best to acquire the knowledge and skills taught." Internal consistency reliability (α) was 0.89.

Instrumentation motivation (also known as utility interest scale) (BYINSTMO). Instrumentation motivation/utility interest measured student's extrinsic motivation to perform well in order to attain goals such as future job opportunities or financial security. This construct was assessed via the following three items: "I study to get a good job"; "I study to increase my job opportunities"; and "I study to ensure that my future will be financially secure." Internal consistency reliability (α) was 0.85.

English self-efficacy (BYENGLSE). English self-efficacy was student's belief about his/her abilities in English and was based on the following four items: "I am certain I can understand the most difficult material presented in English texts"; "I'm confident I can understand the most complex material presented by my English teacher"; "I'm confident I can do an excellent job on my English assignments"; and "I'm confident I can do an excellent job on my English tests." Internal consistency reliability (α) was 0.93.

Math self-efficacy (BYMATHSE). This variable reflects student's self-beliefs about their abilities in math. It was based on the following five items: "I am confident that I can do an excellent job on my math test"; "I'm certain I can understand the most difficult material presented in math texts"; "I'm confident I can understand the most complex material presented by my math teacher"; "I'm confident I can do an excellent job on my math assignments"; and "I'm certain I can master skills being taught in my math class." Internal consistency reliability (α) was 0.93.

Distal outcome variables (also called auxiliary variables). This study sought to understand the relationship between the motivation profiles derived when participating students were in 10th grade, and more distal outcomes: math achievement in 12th grade (collected in 2004), graduation from high school (collected in 2004), postsecondary enrollment immediately following high school graduation (collected in 2006 via interview), and postsecondary completion (collected in 2012).

Achievement in 12th grade (F1TXM1IR). This variable measured achievement in math in 12th grade, collected in 2004 at the first follow-up. The test's level of difficulty for each participant was determined based on the routing test given in 10th grade. The items and scoring was similar to the base year measure. The value was based on item-response theory (IRT) and is the estimated number correct had all 85 items been answered. It is not an integer of the number of items answered correctly, but rather a sum of the probabilities of correct responses if all 85 items were administered and answered

(Ingels et al., 2005). Math achievement is the only measure collected at 12th grade as reading achievement was not collected at the first follow-up.

Graduation from high school (F2F1HSST). This variable measured if participants graduated from high school by the summer of 2004 per the transcript and confirmed during an interview conducted at the second follow-up in 2006. The variable F2F1HSST was coded to include subcategories such as early graduation (in fall 2003), certificate of attendance, GED, unknown status, as well as graduate and no graduate statuses. This researcher renamed the variable (HSGRAD) after collapsing the data in preparation for logistic regression analysis. All students who were coded graduate, including students who graduated in fall of 2003, and students who earned GEDs were re-coded as 1 = Yes. Students who did not graduate, earned certificates of attendance, or whose status could not be determined were re-coded 0 = No.

Post-secondary enrollment (F2PS0409). This variable indicated “enrolled in postsecondary institution in September 2004.” Information was attained from participants during follow-up interviews conducted in 2006. This variable was chosen to reflect post-secondary enrollment because it corresponds with the time period when most students begin their post-secondary education – the fall following graduation. It does not indicate how long the student persisted in post-secondary education, or if they graduated. It was a dichotomous variable coded 1 = Yes (enrolled), 0 = No (not enrolled). The remainder of missing data were due to nonresponse or legitimate skip on item.

Postsecondary completion (F3PSCRED). This variable indicated whether the respondent earned a credential from their last/currently attended post-secondary institution. This information was self-reported and collected in the third follow-up questionnaire in 2012. It is a dichotomous variable. Postsecondary completion was coded 1 = Yes, 0 = No.

Missing data. There was no missing information on covariate variables on participants as a result of two procedures used for ELS:2002 data (NCES, 2017). First, information missing at the time of initial collection at base year (2002) was collected at the first follow up (2004). Second, any information that was not collected at the first follow up was imputed using one of three imputation procedures for missing data: logical imputation, weighted sequential hot deck procedure, and multiple imputation (Ingels et al., 2005). Logical imputation was used for sex and race and determined based on other information provided in the student questionnaire (e.g. sex based on name). Weighted sequential hot deck imputation (Cox, 1980) was used for categorical data for nonresponse items. This method defines imputation classes using cross-classification of covariates to replace missing values for categorical variables. Multiple imputation was used for continuous variables (e.g. 10^{th} grade math and reading achievement, and 12^{th} grade math achievement) (Ingels et al., 2005). Non-respondents from base year (2002) who did not respond to the questionnaire at the first follow up (2004) were removed from the sample thus providing a complete data set for background variables (NCES, 2017).

Latent profile analysis is based on complete responses to question items. "Missing data theory does not apply to exogenous observed variables" (Linda K. Muthén, July 17, 2012) and data was therefore not imputed. Approximately 35% of the participants did not respond to any of the 22 items on the student questionnaire that asked about motivation, the exogenous observed variables. As a result, these cases could not be included in analysis and resulted in an error message reading, "Number of cases with missing on all variables [number of missing cases]." The sample size was thus reduced substantially from 16,197 to 10, 981.

3.4 SAMPLE DESIGN

As previously stated, ELS:2002 used a complex sample design. When a sample is not a simple random sample, design effects have to be accounted for. "The design effect is the ratio of the actual variance of the statistic to the variance that would have been obtained had the sample been a simple random sample" (Ingles et al., 2014, p. 91).

To account for over-sampling certain student samples (stratification), and the effects of sampling these students from within a set number of schools (clustering), variance estimations are made through adjustments via Taylor series variance estimation and require the application of specific variables (STRATID, for student level), and primary sampling units (PSUs, for clustering) to off-set the chance of Type-I error, rejecting the null hypothesis when there is actually no effect (Carlson, Johnson, & Cohen, 1993; Ingles et al., 2014).

Weight. Unlike random sampling where participants have an equal probability of being selected to participate, in complex sample design students are selected, and sometimes oversampled to ensure adequate measures. This creates an unequal probability of selection, which must be compensated for if the results are to be generalizable. Weights are therefore applied. The weights adjust for this unequal probability of being selected as well for non-response bias, which can have an effect on significance testing and lead to Type 1 errors. School weights and student weights are calculated based on probability of selection. These weights are either used for analysis, or are used as the basis to determine other weights, such as panel weights. (Ingles et al, 2004).

Panel weights are used in analyses that span across rounds of data collection in longitudinal studies. Because the motivation variables of interest were collected at the base year (2002) and used for analysis with dependent variables collected in the third follow-up (2012), the panel weight variable F3BYPNWT was selected. Not only does the panel weight account for bias as a result of over-sampling certain populations, it also helps account for non-response adjustments (NCES, 2017).

3.5 ANALYTIC APPROACH

The analysis used for this study was general mixture modeling. Mixture models are based on the premise that the sampled population is comprised of subpopulations, a mix of distributions that represent subpopulations, also referred to as classes, clusters, or profiles, all of which have their own set of parameters (Pastor, Barron, Miller, & Davis, 2007). Under the framework of structural equation modeling, general mixture modeling incorporates a number of models such that it allows for latent class analysis using both categorical and continuous variables (latent profile analysis) with longitudinal data, thus enabling the exploration of effects on more distal outcome variables (Muthén & Muthén, 2000).

To address the research questions, "What motivational profiles are evident within a national sample of 10th grade students?" "How does SES predict class membership?" and "Which motivation profiles best predict outcomes for students at the lowest SES level?" latent profiles analysis were first performed.

Latent profile analysis. Latent profile analysis, considered a person-oriented approach (Bergman & Magnusson, 1997), posits that distinct, but previously unknown subgroups of individuals within a population can be determined based on “latent” or hidden constructs measured indirectly through observed variables, such as ratings on survey items. This reduces large groups into smaller classes or profiles (Collins & Lanza, 2010; DiStefano, 2012; DiStefano & Kamphaus, 2006; Oberski, 2016). Latent profile analysis (LPA) is considered more rigorous and therefore preferred over cluster analysis. Cluster analysis, another person-oriented approach, determines group membership based on centroids to minimize differences between members within the group, while maximizing differences between groups. LPA, on the other hand, uses posterior probabilities to determine profile membership. For LPA, the criteria used to determine the optimal number of classes is more rigorous, thus making it preferred over other methods (DiStefano, 2012; DiStefano & Kamphaus, 2006; Pastor et al., 2007).

Determining optimal number of classes. Mplus software, version 8 (Muthén & Muthén, 1998 - 2017) was used to perform latent profile analysis. To determine the optimal number of classes the specification for analysis was TYPE=MIXTURE, using only the main variables of interest in the model, the 5 motivation variables. The estimator used was ESTIMATOR=MLR, maximum likelihood parameter estimates with standard errors, which is robust to non-normality (Muthén & Muthén, 1998-2017). To obtain the highest parameter estimates and avoid local likelihood maxima, STARTS were increased up to the highest possible number, 10,000 (in most cases), with a convergence criterion value of 0.000001, and SITERATIONS = 500 iterations. In all cases, the best log likelihood values were replicated.

It should be noted that attempts to take sample design into account through analysis TYPE= COMPLEX MIXTURE and CLUSTER=PSU options, were made. However, the application of these options both significantly impacted the model fit indices (indicating a two-class model was optimal) and could not be used consistently for all analyses (i.e. distal outcomes), so TYPE=MIXTURE was used. As such, these analyses are considered "exploratory," and results may not be generalizable.

The relative model fit indices used were Akaike information criteria (AIC), Bayesian information criteria (BIC), adjusted Bayesian information criteria (aBIC), the Vuong-Lo-Mendell-Rubin test (VLMR), and the Lo-Mendell-Rubin test (LMR). The Bootstrap LR difference test (BLRT) could not be used as this information was suppressed when weights were applied.

To determine the model with the optimal number of classes, sequential analyses were performed increasing the number of classes in the model by one, starting with a two-class model. The fit indices of the model with the smaller number of classes were compared to those of the model with one additional class. Better fitting models had smaller AIC and BIC values, while maintaining statistically significant VLMR and LMR values (Geiser, 2010; Lanza, Tan, & Bray 2013). The model with the optimal number of classes was the model with one less class than the model where the VLMR and LMR values became significant. Entropy values, indicating the quality of the classification of the model, were also considered with values close to one indicating high accuracy in classification (Collins & Lanza, 2010; DiStefano, 2012, DiStefano & Kamphaus, 2006; Pastor et al., 2007). In the end, the values of the fit indices were not the sole determinants of the best model. The model with the optimal number of classes not only had the fewest number of classes (parsimony), but also took theory and logic into consideration (Collins & Lanza, 2010; DiStefano, 2012, DiStefano & Kamphaus, 2006; Pastor et al., 2007; Quirk, Nylund-Gibson, & Furlong, 2012).

Members were assigned to classes based on their highest posterior probability (Geiser, 2010). Posterior probability is the likelihood a class member belongs to the class based on their response pattern to survey items, with values closer to one indicating high probability of accurate assignment. Posterior probabilities allow procedures to estimate model parameters (e.g. means, variances, covariances for each k class) using maximum likelihood criteria to determine how well the data fit the final model (Collins & Lanza, 2010; DiStefano, 2012; DiStefano & Kamphaus, 2006; Geiser, 2010; Pastor, Barron, Miller, & Davis, 2007; Vermunt & Magidson, 2002). Posterior probability values were saved for each case and averaged to provide class probabilities for each class, with values closer to one indicating high homogeneity of that class, an indication of being highly distinct other classes (Lanza & Collins 2010). Class assignments were also saved for each case and used in the anayses.

Auxiliary variables. Auxiliary variables can be covariates and/or distal outcomes depending on how they are specified in the model to either predict group member, or to predict distal outcomes (Asparouhov & Muthén, 2014).

The “three-step approach” is gaining popularity for studies using auxiliary variables in mixture model studies that predict group membership, and/or when group membership is used to predict distal outcomes (Asparouhov & Muthén, 2014). This method is preferred because it allows latent class variables to be examined independently of the auxiliary variables, such that the addition of auxiliary variables into the model do not potentially change class membership itself (Asparouhov & Muthén, 2014; Nylund-Gibson, Grimm, Quirk, & Furlong, 2014; Vermunt, 2010). In the three-step approach, the first step performs latent class analysis/latent profile analysis using only the variables of interest. The second step is the creation of the classes based on the posterior probabilities. In the third step, the class becomes a nominal variable, taking into account the measurement error because class member is not 100%, which are recorded as logit values. The auxiliary variable is included into the model during the third step and the multinomial regression is used to predict outcomes. In cases where the outcome variable is class membership, the R3STEP option is specified under AUXILIARY and the covariates are used as the predictor variables. In cases where class membership is used to predict distal outcomes, an additional step must be taken. Specifically, the logits produced in step two, must be entered in the model specifications (by hand), which must be done in a separate/additional analysis specifying DU3STEP (if the outcome is categorical) or BCH (if the outcome is continuous) in the AUXILIARY command. In both cases (if auxiliary variables are used as predictor variable for class membership, or if class membership is used to predict distal outcomes), equality mean testing is used to determine statistically significant differences between group that predict the classes (Asparouhov & Muthén, 2007, 2010, 2014; Nylund-Gibson et al., 2014). For this study, however, use of the three-step approach was not possible because the software was unable to accommodate the panel weight and the logit weights required in the 3rd step simultaneously (Muthén & Muthén, 1998-2017). As such, the multiple pseudo-class draws method was used to analyze the distal outcomes in this study (Wang, Brown, & Bandeen-Roche, 2005).

Pseudoclass draws. The multiple pseudoclass draws approach was used in this study for predicting distal outcomes. The "PC" approach pre-dates the more recent three-step approach (Clark & Muthén, 2009), but has been widely used in studies related to mental health (Lanza, Tan, & Bray, 2013), and education (Ing & Nylund-Gibson, 2013; Nylund-Gibson, Grimm, Quirk, & Fulong, 2014). Although there are some biases in the estimates and standard errors related to this method, (Clark & Muthén, 2009; Muthén & Muthén, 1998-2017), pseudoclass draws has been found to produce good results when entropy is high (Clark & Muthén, 2009; Lanza, Tan, & Bray, 2013).

For this study, after class membership was determined via posterior probabilities, covariates (math achievement in 10th grade, sex, race, urbanicity, SES) were added to the model (as AUXILIARY = R3STEP) to determine how covariates predicted class membership, producing output to be interpreted as multinomial regression (Nylund-Gibson & Masyn, 2011). The output for the multinomial regressions were reported as logits, which were converted to odds ratios for ease of interpretation (Clark & Muthén, 2009; Quirk, Nylund-Gibson, & Furlong, 2013). Next, the class assignments were used as predictor variables to predict distal outcomes (math achievement in 12th grade, high school graduation, enrollment in post-secondary education immediately following graduation, and post-secondary education completion) by specifying AUXILIARY = (E) to use pseudoclass draws. Because classification is based on probabilities and there is an element of uncertainty (i.e. probability of membership is not 100%), this step takes (20) random samples from the data, akin to imputation, but for the missing latent classes (Clark & Muthén, 2009) before predicting distal outcomes, thus the origin of the name for the pseudoclass draws. Equality of means testing was used to determine if class membership predicted outcomes via an omnibus test (Chi-Square for categorical outcome variables, or ANOVA for continuous outcome variables), with pairwise testing between motivation profiles (Clark & Muthén, 2009; Quirk, Nylund-Gibson, & Furlong, 2013).

In addition to equity of means testing, regression analyses were performed in order to provide a more complete understanding of the distal outcomes. Hierarchical multiple regression was completed to determine how motivation class predicted math achievement in 12th grade. Analyses examined outcomes based on the aggregate data (all SES levels together) and then looked at outcomes for just the lowest SES level. For the aggregate data, control variables were added in the first step, motivation classes in the second step, and interactions between motivation level and SES level in the third. For analysis of the lowest SES level, control variables were added in the first step, and motivation profiles were added in the second step. These same steps were used for hierarchical logistic regression analyses conducted to determine how motivation class predicted high school graduation, enrollment in postsecondary education immediately following high school graduation, and postsecondary education completion, all of which are dichotomous variables. These analyses were performed in SPSS, version 8.

CHAPTER 4

RESULTS

4.1 LATENT PROFILE ANALYSIS

Measurement model. The five motivation variables were composite scores based on sub-questions (a-v) of item 89 on the base year student questionnaire. The variables were created through principal factor analysis and standardized with a mean of zero (0) and a standard deviation of one (1) (Ingles et al., 2005). Composite scores were created by ELS:2002 after a factor analysis was undertaken. Coefficients of reliability values ranged from 0.84 to 0.93.

Structural model. Latent profile analysis using Mplus version 8 was conducted using maximum likelihood and based on the five motivation variables of interest: math self-efficacy (BYMATHSE), English self-efficacy (BYENGLSE), control expectation (BYCONEXP), action control (BYACTCTL), and instrumentation motivation (BYINSTMO). The best fitting model was determined using relative fit indices and entropy values after numerous models were run, keeping parsimony in mind.

Table 4.1 provides information from consecutive LPA runs used to determine the best-fitting model. As seen from the table, as classes were increased from the 2-, 3-, and 4-class models, the AIC and BIC values decreased, while MLMR and LMR values remained statistically significant, suggesting improvement in model fit with each additional class. Another indicator of improved fit was the increase in entropy value. The optimal fitting model is generally the model with the highest number of classes, lowest AIC and BIC values, and highest entropy, while maintaining statistically significant *p*-values for the VLMR and LMR. The best-fitting model is confirmed by the model with one less class than the model where the VLMR and LMR values become significant. In this case, the 4-class model was not directly confirmed, but assumed when the 5-class model did not converge. Several attempts were made to get the 5-class model to converge: starts were incrementally increased to the maximum 10,000 and 2500 (for second step), with 500 iterations, but to no avail. The lack of convergence suggested the 4-class model was the optimal fit.

This study included multiple types of analyses. The results from these analyses are organized under the heading of the question they related to. The study focuses on how SES level relates to motivation profiles. As such, the analyses and results speak to this, to the exclusion of other information provided in the process.

4.2 WHAT MOTIVATIONAL PROFILES ARE EVIDENT WITHIN A NATIONAL SAMPLE OF 10^{TH} GRADE STUDENTS?

Per latent profile analysis, classes were extracted based on participants' posterior probabilities, the likelihood a class member belongs to a class based on their response pattern to survey items. The mean of these posterior probabilities yields the class probability and serves as an indicator that members were assigned to the correct class. The four classes in the chosen model had class probabilities ranging from .937 to .974, indicating high accuracy in class assignment. Once the classes were determined, they were named based on their similar attributes. The classes in this study were named based on the constellations of the mean motivation scores, reported as *Z*-scores. The *high* motivation class/profile had 1,249 members and reflected high levels of motivation with average scores at least one standard deviation above the mean for each of the motivation variables. The *moderate* profile/class, had the most members with 6,004, and reflected average scores within one standard deviation above the mean for each of the motivation variables. There were 3,593 members in the *low* profile/class, so named because the mean scores were within one standard deviation below the mean on each of the motivation measures. The *very low* motivation profile/class had average motivation scores exceeding one standard deviation below the mean. Although this class was very small (approximately 1%), it was distinct with 135 members. Table 4.2 provides a summary of the named classes, number and proportion of members, mean scores for each of the motivation variables, and the class probabilities.

Correlation analysis. A correlation analysis was completed on motivation profiles and SES level to determine the level of relationship between these two important sets of variables. There was a clear pattern of relationships between SES level and motivation profiles, with more affluence associated with higher motivation levels and economic disadvantage associated with *low* motivation levels. Specifically, the highest correlation for SES1 (highest SES level) was with the moderate motivation profile ($r = .103$, $p = .01$), indicating students in this SES level were more likely to be moderately motivated. The highest positive correlation for the lowest SES level was with the *low* motivation profile ($r = .102$, $p = .01$), indicating students with less wealth are more likely to be have a *low* motivation profile. There were also inverse relationships between motivation and SES levels and most, but not all, were statistically significant at the .01

level. The strongest inverse relationship was between the highest SES level (SES1) and *low* motivation (r = -.155, p = .01) indicating that more affluent students were less likely to have low motivation. The reverse was indicated with SES4, the lowest SES level, which was negatively correlated with the *high* motivation class (r = .041, p = .01). Interestingly, SES2, the second highest SES level did not have any statistically significant correlations, suggesting that the relationship between motivation profile and economics is more diffuse. SES3, the second lowest SES level was had weak, negative relationships with *high* and *moderate* motivation classes (r = -.030, and -.037, p = .01), and a weak positive relationship with the *low* motivation profile (r = .061, p = .01), indicating that like the lowest SES level, students were less likely to belong to the *high* or *moderate* profiles and more likely to belong to the *low* motivation group, but to a lesser degree. Table 4.3 provides a correlation matrix between SES level and motivation profiles.

4.3 HOW DOES SES PREDICT MOTIVATION CLASS MEMBERSHIP?

Two different analyses were used to answer this question: regression of the covariates on the class profiles, and a chi-square test of independence. Each of these analyses explored how covariates related to the motivation profiles and the distribution of the profiles across SES level.

Covariates. After the optimal class model with four classes determined, covariates were added to the model and regressed on the motivation classes to determine which variables were associated with class membership. Covariates included math achievement (measured in 10^{th} graded), reading achievement (measured in 10^{th} grade), sex, race, geographic location (urban, suburban, or rural), and SES level. While there were findings associated with all the covariates, for purposes of this study, the focus was on SES level as it related to motivation class assignment.

The *low* motivation class was used as the referent group by which the other motivation groups were compared. The referent group for SES level was the lowest SES level (SES4). In Mplus, the statistics for the variables were reported as logits and interpreted as a multinomial regression. For ease of interpretation, these logit values were exponentiated and converted to odds ratios. Table 4.4 is a summary of the logit values (log-odds) with corresponding *p*-values, and odds ratios for each of the statistically significant covariates which was used to interpret findings for SES level and motivation profiles.

After controlling for prior achievement in math, race, sex, geographic location, the odds of being assigned to the *high* motivation profile increase 1.80 times (80%, $p < .001$), if students were the highest SES level. Being from the highest SES level increased the odds of membership in the *moderate* motivation group by 1.520 times (52%, $p < .001$), holding other variables constant. SES level was not predictive of membership into the *very low* motivation group. Table 4.5 provides a summary of the frequency statistics for sex, race, geographic location, and SES level, and the proportion of membership for each motivation class.

Chi square test of independence. The last type of analyses performed was the chi square test for association to determine the degree of relationship (or conversely, independence) of SES level and motivation profile. The assumption is that there is no association between the two categorical variables. The chi-square test of independence was conducted between SES level and motivation profile and there was a statistically significant association between these two variables, X^2 (9) = 347.100, $p < .001$. The Cramer's V = .103, indicating a small effect size.

Table 4.6 provides the expected and actual counts of the individuals in each of the cells that correspond to motivation profile type and SES level. As Table 4.6 illustrates, there was a disproportionate number of students from the *high* motivation profile who were under-represented in the lowest SES level, yet over represented in the highest SES level. Conversely, in the *low* and *very low* profiles, there was under-representation of students at the highest SES level, and an over-representation of students at the lowest SES level. While there is a clear relationship between low SES status and *low* motivation, and high SES status and *high* motivation, the data also show a high degree of distribution of motivation profile types across all levels of socioeconomic status. For example, for SES2 and SES3, the actual count of members of the *high, moderate, low* and *very low* motivation profiles closely align, or are even match exactly the expected number. This speaks to the heterogeneity of motivation profiles in a given population.

4.4 WHICH MOTIVATION PROFILES BEST PREDICT OUTCOMES FOR STUDENTS AT THE LOWEST SES LEVEL?

To address this question, several analytic approaches were used: equality of means testing and regression analyses. Hierarchical multiple regression and hierarchical logistic regression, adding related variables in blocks, were employed to parse out the contributions each related set of variables made to predicting distal educational outcomes. One of these blocks included interaction terms of motivation profiles and SES level to gain understanding as to any synergetic effect any of these combinations might have on outcomes. Finally, regression analyses among students from the lowest SES level was performed to better understand their educational outcomes as compared to the whole population under investigation.

Equality of means test. As part of pseudoclass draws analysis, a equality of means tests was produced. Equality tests of means used a chi square test (χ^2) to determine how class membership predicted distal outcomes: math achievement in 12th grade, high school graduation, enrollment in post-secondary education immediately following high school graduation, and post-secondary education completion. The means were compared across classes using posterior-probability-based multiple imputations (i.e. multiple pseudoclass draws (Clark & Muthén, 2009)) and were interpreted similar to ANOVA. There were three degrees of freedom for the overall test, and one degree of freedom for pairwise tests.

Math achievement in 12th grade. The mean values for math achievement in 12th grade were 40.724 for the *very low* motivation group, 44.621 for the *low* motivation group, 53.094 for the *moderate* group, and 55.893 for the *high* motivation group, which were different to a statistically significant degree overall (χ^2 = 834.418(3), $p < .001$). All values for the motivation classes were significantly different from each other. Table 4.7 provides the pairwise comparisons, the χ^2 and *p*-values.

High school graduation. The variable for high school graduation was coded 1 = Yes for graduation, and 0 = No for no graduation, so the means were interpreted as percentages for successful graduation from high school. The mean graduation rate for the four motivation classes were as follows: *very low* = .663, *low* = .835, *moderate* = .911, and *high* = .942. The omnibus test for equality tests of means for high school graduation was statistically significant (χ^2 = 190.979 (3), $p < .001$), and indicated that class membership predicted graduation from high school. All pairwise comparisons were statistically significant from each other ($p < .001$). Table 4.8 provides the pairwise comparisons, the χ^2 and *p*-values.

Postsecondary enrollment. The variable for postsecondary enrollment was also dichotomous (1 = Yes, 0 = No). As such, the means were interpreted as percentages. The motivation classes had the following rates of enrollment in postsecondary education: *very low* = .768, *low* = .775, *moderate* = .876, and *high* = .909, which were statistically different from each other, overall ($\chi^2 = 124.504$ (3), $p < .001$). However, only some motivation classes were statistically significant from each other. The *very low* motivation group was statistically different from the *high* group ($\chi^2 = 4.871$ (1), $p < .027$), but not from the *low* or *moderate* motivation profiles. The *low* motivation profile was statistically different from the *moderate* profiles ($\chi^2 = 73.023$ (1), $p < .001$), and the *high* motivation class was different to a statistically significant degree than the *low* group ($\chi^2 = 94.856$ (1), $p < .001$) and *moderate* group ($\chi^2 = 8.820$ (1), $p < .001$). In sum, the only groups where enrollment rates into postsecondary education were not statistically different were between the *very low* and *low* profile, or the *very low* and *moderate* profile groups. Table 4.9 provides the pairwise comparisons, the χ^2 and p-values.

Postsecondary education completion. The overall test for equality of means for postsecondary completion was statistically significant ($\chi^2 = 59.027$ (3), $p < .001$), and indicated that motivation class membership predicted completion of a postsecondary degree. Again, the means, interpreted as percentages, show postsecondary completion for each of the four motivation classes as follows: *very low* = .414, *low* = .455, *moderate* = .521, and *high* = .575. Similar to postsecondary enrollment rates, the completion rates for postsecondary education were not statistically different between the *very low* and *low* profile, or the *very low* and *moderate* profile groups, but statistically significant between the other groups. Table 4.8 provides the pairwise comparisons, the χ^2 and p-values. The frequencies of high school graduation, postsecondary enrollment, and postsecondary completion for each motivation class are provided in Table 4.10.

To summarize, the findings of the equality of means test showed that the motivation profiles predicted all the educational outcomes to a statistically significant degree, based on the omnibus test. The four motivation groups were significantly different from each other in predicting math achievement and high school graduation, the *low* and *very low* motivation profiles were similar in predicting postsecondary enrollment and postsecondary completion. Although equality of means provided some information about predictive ability, additional analyses seemed indicated to provide details about the relationship between SES level and motivation profiles.

Regression analyses. In addition to the equality of means testing completed in Mplus, regression analyses were completed in SPSS (version 23) to provide a more complete picture of the data with regard to the relationship between motivation profile and distal outcomes. The panel weight was not applied in SPSS because sample sizes aligned with the samples sizes determined from LPA without the weight, and applying the weight reduced the sample size, indicating that double-weighting may have been an issue when the weight was applied in SPSS. The regression analyses followed protocols as outlined by Laerd Statistics (2015).

Hierarchical multiple regression. Hierarchical multiple regression was performed to determine how motivation class membership predicted math achievement in

12th grade, a continuous variable. Unlike multiple regression, where all of the independent variables are added in one step, the independent variables were added in steps (blocks) to control for the effects of covariates and to better understand how related variables explained the variance in math achievement in 12th grade. As such, independent variables were added into the regression model to see the effect of each of the variables on the dependent variable, keeping the referent group out of the model for interpretation purposes. The referent group for sex was female, White for race, suburban for geographic location (urbanicity), and the lowest SES level (4th quartile). In the first step (block 1), covariates were added: math achievement in 10th grade, sex (male), race (Native American, Asian, African American, Hispanic – no race affiliation, Hispanic – with race affiliation, Mixed race), urbanicity (urban, rural), and SES level (SESQ1 (highest), SESQ2, SES3). Motivation classes (*high*, *moderate*, *very low*) were added in the second step (block 2) to determine the effect motivation classes had on predicting math achievement in 12th grade. Finally, interaction terms were added in the third step (block 3) to determine if interactions between motivation level and SES level and to understand the significance of any interactions on the dependent variable. There were a total of 12 interactions entered into the model. Each motivation class was multiplied with each SES level, keeping low motivation at each SES level out as the referent group. The interactions were as follows: high motivation * SESQ1 (high), *moderate* motivation * SESQ1, *very low* motivation * SES1; high motivation * SESQ2 (upper middle class), *moderate* motivation * SESQ2, *very low* motivation * SESQ2; high motivation * SESQ3 (lower middle class), *moderate* motivation * SESQ3, *very low* motivation * SESQ3; high motivation * SESQ4 (low), *moderate* motivation * SESQ4, and *very low* motivation * SESQ4.

All assumptions were checked. There was independence of observations per design, and visual inspection of the scatterplot indicated a strong linear relationship between the dependent variable (math achievement in 12^{th} grade) and the only other continuous variable in the model, math achievement in 10^{th} grade. The assumption of homoscedasticity, however, was violated and there was a decreasing funnel shape on the residuals graph. The skewness of the studentized residuals was .142, and because modifications were only for moderately or strongly skewed distributions, the data were not transformed as to not over-correct. Heteroscedasticity could weaken the generalizability of the results. Although there was a high correlation between math achievement in 10^{th} grade and math achievement in 12^{th} grade (r = .903), VIF values were within the acceptable value range (below 10) with the highest VIG value being 6.417, so multicollinearity was not violated. There were 126 outliers (about 1%) in the sample that exceeded ±3 standard deviations for studentized residuals, but leverage points were well within the acceptable .2 "safe" range, with the highest value = .05362. Cook's Distance, an indicator of influential points, was also well within the acceptable range, below 1 (highest value = .04306). Taking all the indices of unusual points into consideration, cases were deemed to not negatively impact results and were retained for analyses. Lastly, the assumption of normality was met: residuals were normally distributed on the histogram, and P-P plot aligned with the diagonal graph.

The full regression model with all of the variables to predict math achievement in 12^{th} grade was statistically significant, $R^2 = .824$, $F(25, 9357) = 1{,}746.327$, $p < .001$, adjusted $R^2 = .823$. As expected, the covariates in step 1 contributed the most in predicting math achievement in 12th grade. Specifically, approximately 82% ($R^2 = .822$, adjusted $R^2 = .821$) of the variance was explained by math achievement in 10th grade, sex, race, urbanicity, and SES variables, which was statistically significant ($p < .001$). Adding motivation classes to the model improved the model slightly, but to a statistically significant degree, by increasing the variance by .002 ($R^2 = .823$, $p < .001$). Adding interactions into the model did not contribute at all to predicting math achievement in 12th grade ($R^2 = .823$, $p = .259$).

Based on the results of the full model, the coefficients for SES level and motivation profile were interpreted with a higher degree of focus, as these variables were of greatest interest. SES level was statistically significant in predicting math achievement in 12th grade, when other control variables were held constant. Compared to the lowest SES level, students from the highest SES level (SES 1, the 1st quartile) were predicted to score 2.003 ($p < .001$) points higher, while students from the 2nd and 3rd quartiles were predicted to score 1.521 ($p < .001$) points and .956 ($p < .01$) above peers from the lowest (4th) quartile, holding all other variables constant. As previously stated, motivation class membership also contributed to the model in predicting math achievement in 12th grade. Membership in the *high* motivation class predicted a 2.457 ($p < .001$) point increase in math achievement in 12th grade over those in the *low* motivation class, and an increase of 1.826 ($p < .001$) points if students belonged to the *moderate* motivation class, relative to the *low* motivation class, holding all other variables constant. Students in the *very low* motivation group were similar to their peers in the *low* motivation class. Because interactions did not contribute to the model, these coefficients were not interpreted. Other covariates predicted math achievement in 12th grade: math achievement in 10th grade, identifying as male, Asian, and attending an urban school predicted more favorable outcomes to a statistically significant degree, compared to their referent groups and holding other variables constant. Table 4.11 provides a list of each of the variables entered at each step, the unstandardized and standardized beta values, and whether or not they are significant, along with R^2 and F values and changes in these values.

Hierarchical multiple regression for math achievement in 12th grade for students at the lowest SES level. Hierarchical multiple regression was completed exclusively for students from the lowest SES level (split out) to examine how motivation profiles relate to outcomes within this focal subsample. As with the previous hierarchical multiple regression, the covariates (math achievement in 10th grade, sex, race, urbinacity) were added in the first block, except for SES level. The model predicted math achievement in 12th grade to a statistically significant degree, $F(13, 1788) = 482.399$, $p < .001$, and explained approximately 78% of the variance ($R^2 = .776$, adjusted $R^2 = .775$). The model's ability to predict math achievement improved after the second step, the addition of the motivation profiles, $F(3, 1788) = 5.122$, $p = .002$, and explained an additional $R^2 = .002$. The coefficients for the full model predicted that membership into the *high* motivation group at the lowest SES level predicted an increase in of 1.127, $p = .027$ points in math achievement, and an increase of 1.124, $p = .046$ points if students were members of the *moderate* profile, holding all other variables constant. As with the model using aggregate data, math achievement in 10th grade, being male and identifying as Asian were also statistically significant in predicting math achievement in 12th grade, although urbanicity was not. The variables entered in each step of the hierarchical multiple regression and the unstandardized beta coefficients used for interpretation are in Table 4.12

Hierarchical logistic regression. Hierarchical logistic regression was performed to determine if motivation class membership predicted distal outcomes on measures that were dichotomous. The three dichotomous dependent variables, high school graduation, enrollment in post-secondary education the autumn following graduation, and completion of post-secondary education were coded 1 = Yes, 0 = No.

As with hierarchical multiple regression, variables were added in steps (blocks) to control for the effects of the covariates and to better understand how related variables explained the variance in each of the three dependent variables. The referent group for sex was female, White for race, suburban for geographic location (urbanicity), and the lowest SES level (4^{th} quartile). In the first step (block 1), covariates were added: math achievement in 10^{th} grade, sex (male), race (Native American, Asian, African American, Hispanic – no race affiliation, Hispanic – with race affiliation, Mixed race), urbanicity (urban, rural), and SES level (SESQ1 (highest), SESQ2, SES3). Motivation classes (*high*, *moderate*, *very low*) were added in the second step (block 2) to determine the effect motivation classes had on predicting math achievement in 12^{th} grade. Finally, interaction terms were added in the third step (block 3) to determine if interactions between motivation level and SES level and to understand the significance of any interactions on the dependent variable. There were a total of 12 interactions entered into the model. Each motivation class was multiplied with each SES level, keeping *low* motivation at each SES level out as the referent group. The interactions were as follows:

high motivation * SESQ1 (high), *moderate* motivation * SESQ1, *very low* motivation * SES1; *high* motivation * SESQ2 (upper middle class), *moderate* motivation * SESQ2, *very low* motivation * SESQ2; *high* motivation * SESQ3 (lower middle class), *moderate* motivation * SESQ3, *very low* motivation * SESQ3; *high* motivation * SESQ4 (low), *moderate* motivation * SESQ4, and *very low* motivation * SESQ4.

All assumptions were checked. Multicollinearity between the independent variables were checked for each dependent variable. Multicollinearity did not appear to be a problem as VIF values did not exceed 1.2 between any of the independent variables. The linearity assumption using the Box Tidwell test were all non-significant, indicating linearity between the dependent variables and math achievement in 10th grade. Linearity between the dependent variables and categorical variables was not applicable. All outliers were retained in the data for analyses (only applicable for high school graduation, where there were six outliers). Tables 4.13, through 4.18 provide the hierarchical logistic regression results of the each of the dichotomous outcome variables: high school graduation, post-secondary enrollment, and post-secondary completion and all relevant information on which the following interpretations were based. While the odds ratios were provided for all the covariates, because this study is interested in SES level and motivation class membership, only those odds ratios were interpreted.

Logistic regression of high school graduation (HSGRAD). The full model with all of the variables to predict high school graduation examined. It was statistically significant, X^2 = 1081.199 (25), p < .001, and explained almost 19% of the variance (Nagelkerke R^2 = .188). The block (block 0) predicted 89.1% accuracy of correct classification for high school graduation without any predictor variables. The addition of the control variables (sex, race, geographic location, and SES level) did not improve the model's accuracy, which remained at 89.1. The model had a 2.8 accuracy rate of predicting students would not graduation from high school, only correctly predicting 34/1196, while the accuracy rate of correctly predicting high school graduation was 99.6%, correctly predicting 9743/9781. The Hosmer and Lemeshow test was significant (p = .027), indicating a poor fit with the data. The predictor variables explained almost 18% of the variance in high school graduation (Nagelkerke R^2 = .179). The addition of the motivation classes into the model (step 2) did not improve the model's accuracy in predicting high school graduation, but the omnibus test remained statistically significant with the addition of the step, X^2 = 44.314 (3), p < .001, and increased the variance by .008 (Nagelkerke R^2 = .187). The Hosmer and Lemeshow test was significant with the addition of these variables, indicating an improvement in fit with the data. When the interaction terms were added in the third step (block 3), the variance remained virtually unchanged (Nagelkerke R^2 = .188) and the omnibus test was no longer statistically significant, X^2 = 10.246 (9), p = .331. Additionally, the Hosmer and Lemeshow Test became statistically significant, indicating that the addition of the variables made the data fit less well than the previous model.

Because the addition of the third step (block) was not statistically significant, the log ratios (Exp(B)) values for second step (block) were interpreted giving attention to SES level and motivation profile. The odds of graduation from high school increased 2.415 times (70.7%, p < .001), 1.928 times (92.8%, p < .001), and 1.411 times (41.1%, p < .001), for students who came from households in the highest earning SES quartile (SES1), the 2nd highest (SES2), and 2rd lowest (SES3) quartiles respectively, relative to the lowest SES quartile, holding other variables constant. As previously noted, motivation class was a significant predictor of high school graduation. The odds of graduating high school increased 1.794 times (79.4%, $p < .001$) for members of the *high* motivation profile, and 1.342 times (34.2%, $p < .001$) for students with *moderate* motivation profiles, compared to the *low* motivation profile, holding all other variables constant. Comparatively, students from the *very low* motivation group were at .497 times reduced odds ($p < .001$) of graduation, holding other variables constant. Math achievement in 10^{th} grade predicted high school graduation, while male students as well as those identifying as Native American, Hispanic, and mixed race were less likely to do so. See Table 4.13 for details.

Hierarchical logistic regression of high school graduation for students at the lowest SES level. Additional analyses were completed looking specifically at high school graduation of students in the lowest SES level (SES4). In the first step control variables were added into the model (math achievement in 10^{th} grade, sex, race, and urbanicity). This model without any predictor variables had an accuracy rate of 75%, which increased to 78.8% after the control variables were added. The omnibus test was statistically significant, $X^2 = 176.559$ (10), $p < .001$. Variance explained was 11% (Nagelkerke $R^2 = .114$), and the Hosmer & Lemeshow test was not significant at .172, indicating a good fit with the data. The second step, the addition of the motivation classes, was also statistically significant, $X^2 = 14.169$ (3), $p = .003$, and explained an additional .009 in variance. The accuracy of the model increased to 79%, correctly predicting that students did not graduate from high school only 3.3% of the time (16/491), but correctly predicting students graduated 99.4% of the time (1816/1827). For students at the lowest

SES level, only belonging to the *moderate* motivation group predicted high school graduation. The odds of students in this motivation profile graduating high school was increased 1.458 times (45.8%, p = .005). Again, math achievement in 10th grade predicted graduation and male students were less likely to graduate than females, holding other variables constant. Table 4.14 provides details about the odds ratios.

Logistic regression of post-secondary enrollment. The model without any independent variables had an accuracy rate of 86.7% in predicting students would enroll in postsecondary education immediately following high school graduation. When the control variables were added (math achievement in 10th grade, sex, race, urbanicity, SES level) the model's ability to accurately predict the outcome did not improve, however the model statistically significant X^2 = 660.247 (13), p < .001, and explained 15% of the variance (Nagelkerke R^2 = .154). The Hosmere and Lemeshow test was .205, indicating the data fit the model. The addition of the second step, the motivation profiles, did not improve the model's accuracy rate, but it explained .009% more variance (Nagelkerke R^2 = .163) and the step contributed to a statistically significant degree, X^2 =42.473 (3), p < .001. The Hosmere and Lemeshow test was .241. The addition of the interaction terms in the third step did not contribute to the model to a statistically significant degree X^2 = 7.369 (9), p < .599. As such, the Exp(B) values for the second model were interpreted, looking specifically at SES level and motivation profiles.

As with high school graduation, SES level and motivation profile predicted enrollment in postsecondary education. Students from the highest SES level had the highest odds of enrollment at 2.612 times (72.3%, p < .001), and even higher odds of 1.789 times (78.9%, p < .001) for students at the 2nd highest quartile, and 1.286 times

(28.6%, p = .013) for students in the 2nd lowest SES (Q3) quartile compared to the lowest SES quartile, holding other variables constant. As previously stated, motivation class added to the accuracy of the model, overall. The odds of postsecondary enrollment increased 1.814 times (81.4%, p < .001) for students in the *high* motivation class, and 1.583 times (58.3%, p < .001) for those from the *moderate* motivation class compared to the *low* motivation class, holding all other variables constant. There was no statistical difference between the *low* and *very low* motivation groups. Math achievement in 10th grade predicted postsecondary enrollment, while being male and identifying as Hispanic decreased the odds compared to referent groups, holding other variables constant. Table 4.15 provides the odds ratios and significance levels for each of the variables entered in steps in the hierarchical logistic regression predicting postsecondary enrollment.

Hierarchical logistical regression for postsecondary enrollment for students at the lowest SES level. As with high school graduation, additional analyses were completed looking at postsecondary enrollment of those at the lowest SES level, using the same steps as previously described. Without any predictor variables, the model predicted a 75% accuracy rate of postsecondary enrollment, which declined to 74.4% after the control variables were added. None-the-less, the model was statistically significant at predicting, $X^2 = 96.139$ (10), $p < .001$, and explained 12% of the variance, (Nagelkerke $R^2 = .121$). The Hosmer and Lemeshow test was .742. The addition of the motivation profiles in step two increased the accuracy of the model to a statistically significant degree, $X^2 = 7.708$ (3), $p = .052$, and explained an additional .009 in variance (Nagelkerke $R^2 = .130$). Similar to the hierarchical logistic regression analysis for students at the lowest SES level that predicted high school graduation, relative to the *low* motivation class, the only motivation class that increased the likelihood of enrollment in postsecondary education was the *moderate* motivation profile, which increased the odds by 1.543 (54.3%, p = .005), holding all other variables constant. Increased math achievement in 10th grade improved the odds of enrollment in postsecondary education, as did identifying as Asian, while being male decreased the odds, compared to the referent groups and holding other variables constant. See Table 4.16 for details.

Hierarchical logistic regression for post-secondary education completion. As with the other hierarchical logistic regression, the models were examined as blocks of variables added into the model. The model predicting postsecondary completion modestly improved from 52.9% accuracy to 60.1% accuracy after adding math achievement in 10th grade, sex, race, geographic location, SES level. This model was statistically significant with an omnibus test of X^2 = 451.512 (13), p = .001, which explained only 7% of the variance (Nagelkerke R^2 = .073). The Hosmer and Lemeshow test was not statistically significant (p = .378), suggesting an adequate fit with the data. Adding the motivation profiles into the second step (block 2) increased the accuracy of the model nominally, to 60.3%, but to a statistically significant degree X^2 = 8.118 (3), p = .044. It had a 70.6% accuracy rate of predicting postsecondary completion (3017/4272), and a 48.6% accuracy rate of correctly predicting that students would not earn a postsecondary degree (1953/3801). The addition of the interaction terms did not contribute to the model, X^2 = 10.027 (9), p = .348, so was not considered when interpreting Exp (B) values which focused on SES level and motivation class membership in predicting postsecondary completion.

Consistent with the other outcomes, SES level and motivation profile were statistically significant predictors of post-secondary education completion. Again, holding all other control variables constant, SES levels predicted postsecondary completion: Students from the top two quartile of SES level had increased odds of 1.590 times (59.0%, $p < .001$), and 1.216 times (21.6%, $p = .008$) relative to low SES of completing a postsecondary degree, when other variables were held constant. Students in the *high* motivation class and *moderate* motivation class had increased odds of completing a postsecondary degree of 1.216 times (21.6%, p=.014), and 1.122 times (12.2%, p=.033) relative to the *low* motivation group, holding all other variables constant. As with other outcomes, higher math achievement in 10th grade increased the odds of postsecondary completion, while being male, African American, or Hispanic decreased the odds, compared to referent groups and holding other variables constant. Table 4.17 provides the odds ratios and significance levels for each of the variables entered in steps in the hierarchical logistic regression predicting postsecondary completion.

Hierarchical logistic regression for postsecondary completion of students at the lowest SES level. To predict postsecondary completion for students at the lowest SES level, hierarchical logistic regression was completed, using the same step as above: step one adding the control variables, and step two adding the motivation profiles. Similar to the analyses above, the model without any predictor variables had an accuracy rate of 53.3%, which improved to 58.5% when the control variables were added in the first step. This model predicted the outcome to a statistically significant degree $X^2 = 66.211$ (10), $p < .001$, and explained 5% of the variance (Nagelkerke $R^2 = .049$). The data fit the model, as indicated by the Hosmer and Lemeshow test at .871. The addition of the motivation profiles in step two did not improve the model, $X^2 = 2.303$ (3), $p = .512$ and none of the motivation profiles were able to predict completion of a post-secondary degree. Consistent with all other outcomes, math achievement in 10th grade was a significant predictor in postsecondary completion, while males were less likely than females to achieve outcome when other variables were held constant, but race was not a factor. See table 4.18 for details about the odds ratios for the hierarchical logistic regression predicting postsecondary completion for the lowest SES level. Table 4.19 provides frequencies for each of the predictors/control variables for each of the outcomes of the hierarchical logistic regression analyses. Table 4.20 provides the frequencies of high school graduation, postsecondary enrollment, and postsecondary completion for each motivation class.

To summarize, hierarchical regression analyses were completed to examine how control variables and motivation profiles differentially added to the model's ability to predict math achievement in 12th grade, high school graduation, postsecondary enrollment, and postsecondary completion. Interactions between SES level and motivation level were also examined. The interactions were not significant, and therefore were not further considered or interpreted. The outcome measures were examined for the entire population under investigation, using the lowest SES level as the referent group. The outcomes for the lowest SES quartile were then examined in isolation in order to ascertain how that group fares in comparison to their more affluent peers. SES level predicted favorable outcomes. Generally speaking, the higher the SES level the higher the math achievement scores and better odds for graduating high school, enrolling in postsecondary education, and completing postsecondary education. This was also true of motivation class membership for the entire population in the ELS:2002 data: The *high* and *moderate* motivation profiles consistently predicted the higher the math achievement scores, as well as higher odds of graduating from high school, enrolling in postsecondary education, and completing post-secondary education. However, motivation profiles for students in the lowest SES did not consistently predict these outcomes. The *high* and *moderate* motivation profiles for students in the lowest SES quartile predicted math achievement scores on par with the aggregate of students, indicating that all students, regardless of SES level are able to achieve to higher levels with higher levels of motivation. What was not expected was that only the *moderate* motivation profile was able to predict high school graduation and postsecondary enrollment, and motivation profile was not predictive of postsecondary completion at all. It is not clear why the *high* motivation profile did not predict outcomes over the *moderate* group, but lack of power due to small numbers might explain this unexpected finding. Other covariates also predicted educational outcomes, but were not expounded upon as they were of less interest in this particular study.

This chapter discussed a number of different types of statistical analysis involved in this study, including the latent profile which extracted motivation profile on which much of these analyses are based. Taken together, the analyses illustrate a common theme. First, covariate analyses demonstrated that being from the SES level predicted membership into motivation profile, with highest SES membership predicting membership into the *high* and *moderate* motivation profiles. The equality of means test showed how motivation profiles predicted educational outcomes: math achievement in 12th grade, high school graduation, enrollment in postsecondary education immediately following graduation, and postsecondary completion, with *high* and *moderate* motivation profiles consistently predicting these outcomes, while *low* and *very low* profiles not being statistically different from each other in predicting postsecondary enrollment and completion. Correlation analyses between SES level and motivation profiles indicated a relationship between these two variables, the strongest relationships being an inverse relationship between high SES level and *low* motivation, and low SES level and *high* motivation. These findings were mirrored in the chi-square test which also spoke to the disproportionate number of students with *low* and *very low* motivation profiles from the lowest SES level, and inversely, high numbers of students from the *high* motivation profile from the highest SES level. Additionally, the chi-square test also showed that, while there is a clear relationship between SES level and motivation, there is also variability in motivation profiles at every SES level. Finally, the regression analyses demonstrated how both high SES level and *high* and *moderate* motivate profiles bode well for educational outcomes, and moreover, even for those in the lowest income level, a *high* motivation profile predicted as favorable an outcome for math achievement and high school graduation as other SES levels.

Table 4.1

Model runs to determine optimally fitting model

N = 10,981						
Classes	Log Likelihood	AIC	BIC	VLMR p-value	LMR p-value	Entropy
2	-65502.316	131046.633	131200.017	0.0000	0.0000	0.830
3	-61568.864	123201.727	123435.456	0.0000	0.0000	0.876
4	**-60252.894**	**120591.788**	**120905.860**	**0.0046**	**0.0051**	**0.904**
5	Convergence was not achieved					

Note. Bold indicates optimal fitting model.

Table 4.2

Class names, means of motivation variables on which classes were determined, and class probability values

	Profile/Class Names			
N = 10,981	*High*	*Moderate*	*Low*	*Very Low*
	n = 1249	*n* = 6004	*n* = 3593	*n* = 135
Means	(11.4%)	(54.7%)	(32.7%)	(1.2%)
BYMATHSE	1.156	0.246	-0.704	-1.817
BYENGLSE	1.257	0.266	-0.782	-2.11
BYCONEXP	1.382	0.371	-0.964	-2.446
BYINSTMO	1.425	0.215	-0.778	-1.791
BYACTCTL	1.518	0.284	-0.910	-2.243
Class Probability	0.947	0.945	0.937	0.974

Table 4.3

Correlation matrix between motivation profile/class and SES level, using Spearman's Rho

SES level	SES1 High	SES2	SES3	SES4 Low
High	.075**	-.011	-.030**	-.041**
Moderate	.103**	-.001	-.037**	-.077**
Low	-.155**	.009	.061**	.102**
Very Low	-.028**	-.003	- .001	.036**

**correlation is significant at the .01 level

Table 4.4

Covariates as they predict membership to class using low as referent group

	High			*Moderate*			*Very Low*		
Variable	Log-Odds	*p*-Value	Odds Ratio	Log-Odds	*p*-Value	Odds Ratio	Log-Odds	*p*-Value	Odds Ratio
Achievement:									
Math Ach (10th)	**0.065**	**0.001**	**1.067**	**0.042**	**0.001**	**1.043**	-0.008	0.664	0.992
Read Ach (10th)	**0.026**	**0.001**	**1.026**	**0.030**	**0.001**	**1.030**	**-0.040**	**0.054**	**1.041**
F1SEX: (F)	**0.265**	**0.008**	**1.303**	**0.207**	**0.003**	**1.231**	0.174	0.470	1.190
Race: (White)									
Native Amer.	0.113	0.841	1.142	0.235	0.490	1.267	**-17.131**	**0.001**	**3.632^8**
Asian	0.283	0.083	1.327	0.099	0.442	1.105	-0.105	0.804	0.900
African Amer.	**1.369**	**0.001**	**3.935**	**0.790**	**0.001**	**2.207**	-0.460	0.323	0.631
Hispanic	**0.823**	**0.001**	**2.277**	**0.535**	**0.001**	**1.714**	-0.237	0.653	0.789
Hispanic	**0.810**	**0.001**	**2.248**	**0.399**	**0.007**	**1.491**	-0.214	0.619	0.807
2+ Race	-0.259	0.304	0.772	-0.132	0.423	0.877	0.293	0.557	1.340
Urbanicity: (Suburban)									
Urban	0.287	0.013	1.332	**0.195**	**0.018**	**1.215**	-0.138	0.616	0.871
Rural	0.071	0.586	1.074	-0.020	0.817	0.981	-0.137	0.668	0.872
SES (Low)									
SES Q2	0.028	0.848	1.028	0.082	0.339	1.085	-0.202	0.538	0.817
SES Q3	0.076	0.617	1.079	0.102	0.304	1.107	0.036	0.916	1.037
SES Q4	**0.588**	**0.001**	**1.800**	**0.419**	**0.001**	**1.520**	-0.011	0.978	1.011

Bold indicates statistical significance at the .05 level or above

Table 4.5

Descriptive statistics of motivation profile indicating sex, race, geographic location (urbanicity), and SES quartile

N = 10,981	*High* n = 1249 (11.4%)	*Moderate* n = 6004 (54.7%)	*Low* n = 3593 (32.7%)	*Very Low* n = 135 (1.2%)
SEX N = 10,981				
Male	570 (45.6%)	2753 (45.9%)	1759 (49.0%)	63 (46.3%)
Female	679 (54.4%)	3250 (54.1%)	1834 (51.0%)	73 (53.7%)
RACE N = 10,984*				
White	792 (63.4%)	4038 (67.3%)	2340 (65.1%)	87 (64.0%)
Native American	7 (0.6%)	46 (0.8%)	34 (0.9%)	0 (0.0%)
Asian	60 (4.8%)	240 (4.0%)	129 (3.6%)	5 (3.7%)
African American	182 (14.6%)	672 (11.2%)	366 (10.2%)	11 (8.1%)
Hispanic (no race)	75 (6.0%)	365 (6.1%)	241 (6.7%)	10 (7.4%)
Hispanic (race)	96 (7.7%)	401 (6.7%)	284 (7.9%)	12 (8.8%)
More than 1 race	38 (3.0%)	242 (4.0%)	200 (5.6%)	11 (8.1%)
URBANACITY N = 10,981				
Urban	379 (30.3%)	1662 (27.7%)	888 (24.7%)	31 (22.8%)
Suburban	635 (50.8%)	3179 (53.0%)	1924 (53.5%)	77 (56.6%)
Rural	235 (18.8%)	1162 (19.4%)	781 (21.7%)	28 (20.6%)
SES QUARTILE N = 10,977*				
SES1 (lowest quartile)	225 (18.0%)	1165 (19.4%)	1000 (27.8%)	45 (33.1%)
SES2 (2nd lowest)	263 (21.0%)	1419 (23.7%)	993 (27.6%)	34 (25.0%)
SES3 (2nd highest)	307 (24.6%)	1591 (26.5%)	948 (26.4%)	37 (27.2%)
SES4 (highest quartile)	455 (36.4%)	2950 (26.9%)	652 (18.1%)	20 (14.7%)

*Number of cases is different from total count because cell counts were rounded

Table 4.6

Chi square test for SES level and motivation profile

	Motivation Profile			
	High	Moderate	Low	Very Low
SES Level	Exp/Count	Exp/Count	Exp/Count	Exp/Count
SES1 (lowest)	264.2 / 206	1286 / 1115	741.8 / 954	26 / 43
SES2	290.6 / 246	1413.7 / 1329	816 / 947	28.6 / 28
SES3	320.6 / 304	1560.6 / 1559	900 / 920	31.5 / 30
SES4 (highest)	375.6 / 495	1828.6 / 2087	1054.8 / 692	36.9 / 22

X^2 (9) = 347.100, $p < .001$. Cramer's V = .103, indicating a small effect size.

Table 4.7

Equality of means results for math achievement in 12th grade

Omnibus test: $\chi^2 = 834.418$ (3), $p < .001$

Comparison groups	Chi-Square	*p*-value
Very low vs. low	9.269	**<0.001**
Very low vs. moderate	94.950	**<0.001**
Very low vs. high	126.474	**<0.001**
Low vs. moderate	553.726	**<0.001**
High vs. low	409.865	**<0.001**
High vs. moderate	26.867	**<0.001**

Bold indicates statistical significance at the .05 level or above

Table 4.8

Equality of means results for high school graduation

Omnibus test: $\chi^2 = 190.979$ (3), $p < .001$

Comparison groups	Chi-Square	*p*-value
Very low vs. low	16.455	**<0.001**
Very low vs. moderate	35.170	<**0.001**
Very low vs. high	43.451	<**0.001**
Low vs. moderate	82.418	<**0.001**
High vs. low	117.617	<**0.001**
High vs. moderate	13.902	<**0.001**

Bold indicates statistical significance at the .05 level or above

Table 4.9

Equality of means results for post-secondary enrollment

Omnibus test: $\chi^2 = 124.504$ (3), $p < .001$

Comparison groups	Chi-Square	*p*-value
Very low vs. low	0.014	0.906
Very low vs. moderate	2.926	0.087
Very low vs. high	4.871	**0.027**
Low vs. moderate	73.023	<**0.001**
High vs. low	94.856	<**0.001**
High vs. moderate	8.820	<**0.001**

Bold indicates statistical significance at the .05 level or above

Table 4.10

Equality of means for post-secondary education completion for each SES level

Omnibus test: $\chi^2 = 59.027$ (3), $p < .001$

Comparison groups	Chi-Square	*p*-value
Very low vs. low	0.490	0.484
Very low vs. moderate	3.465	0.063
Very low vs. high	7.389	**0.007**
Low vs. moderate	26.225	<**0.001**
High vs. low	41.748	<**0.001**
High vs. moderate	9.528	**0.002**

Bold indicates statistical significance at the .05 level or above

Table 4.11

Hierarchical Multiple Regression Predicting math achievement in 12^{th} grade from control variables, motivation class, and interaction effects of motivation level and SES levels

	Math Achievement in 12^{th} Grade					
	Model 1		Model 2		Model 3	
Variable	B	ß	B	ß	B	ß
STEP 1: Control Variables						
Math Achieve 10^{th}	1.109	.870***	1.094	.858***	1.094	.858***
Male	.578	.019***	.633	.021***	.631	.021***
Native American	-1.371	-.008	-1.349	-.007	-1.387	-.008
Asian	1.246	.025***	1.210	.025***	1.206	.024***
African American	-.624	-.013**	-.845	-.017***	-.825	-.017***
Hispanic (no race)	-.701	-.011	-.869	-.013**	-.841	-.013**
Hispanic (race)	.513	.009	.390	.007	.395	.007
Mixed	.102	.001	.130	.002	.148	.002
Urban	.577	.018***	.509	.016***	.505	.016***
Rural	-.450	-.012**	-.457	-.012**	-.457	-.012**
SESQ1 (high)	2.679	.084***	2.522	.079***	2.003	.063***
SESQ2	1.521	.045***	1.453	.043***	1.521	.045***
SESQ3	.850	.024***	.817	.023***	.956	.024**
STEP 2: Motivation Class						
High Motivation			1.799	.039***	2.457	.053***
Moderate Motivation			1.261	.042***	1.826	.061***
Very Low Motivation			-.653	-.004	.042	.000
STEP 3: Interaction of Motivation and SES level						
Very Low * High SES					-.035	.000
High Mot * Upper Mid					-1.158	-.013*
Mod * Upper Mid					-.685	-.016
Very Low * Upper Mid					-.739	-.002
High * Lower Mid					-.373	-.004
Mod * Lower Mid					-.962	-.021**
Very Low * Lower Mid					-2.066	-.007
High * Low					1.249	-.001
Mod * Low					-.597	-.012

*signifies ($p < .05$), ** signifies ($p < .001$), *** signifies ($p < .001$)

Table 4.12

Hierarchical multiple regression for lowest SES level predicting math achievement in 12th grade from control variables, motivation class, and interaction effects of motivation

	Math Achievement in 12th Grade			
	Model 1		Model 2	
Variable	B	ß	B	ß
STEP 1: Control Variables				
Math Achieve 10th	1.094	.875***	1.082	.866***
Male	.302	.001	.375	.014***
Native American	1.466	.011	1.472	.011
Asian	1.485	.038**	1.439	.037**
African American	- .196	-.005	- .428	-.011
Hispanic (no race)	.362	.009	.231	.006
Hispanic (race)	.666	.016	.549	.013
Mixed	- .946	-.014	- .936	-.014
Urban	.471	.016	.420	.015
Suburban	.231	.008	.248	.009
STEP 2: Motivation Class				
High Motivation			1.127	.027**
Moderate Motivation			1.124	.046***
Very Low Motivation			.079	.001

Table 4.13

Hierarchical Logistic Regression Predicting high school graduation from control variables, motivation class, and interaction effects of motivation level and SES levels

	High School Graduation					
	Model 1		Model 2		Model 3	
Variable	B	Exp(ß)	B	Exp(ß)	B	Exp(ß)
STEP 1: Control Variables						
Math Achieve 10th	.070	1.072***	.065	1.067***	.065	1.067***
Male	-.510	.600***	-.487	.614***	-.491	.612***
Native American	-.716	.489**	-.724	.485**	-.729	.483**
Asian	-.090	.914	-.124	.884	-.127	.880
African American	.008	1.008	-.081	.922	-.081	.922
Hispanic (no race)	-.340	.712***	-.403	.668***	-.401	.669***
Hispanic (race)	-.269	.764**	-.329	.720***	-.331	.718**
Mixed	-.438	.645***	-.446	.640***	-.450	.637***
Urban	.031	1.031	.020	1.020	.013	1.013
Suburban	.053	1.055	.062	1.064	.061	1.063
SESQ1 (high)	.928	2.529***	.882	2.415***	.806	2.239***
SESQ2	.670	1.955***	.656	1.928***	.693	1.999***
SESQ3	.357	1.429***	.345	1.411***	.313	1.367**
STEP 2: Motivation Class						
High Motivation			.584	1.794***	.351	1.421
Moderate Motivation			.294	1.342***	.300	1.350**
Very Low Motivation			-.698	.497***	-.584	.557
STEP 3: Interaction of Motivation and SES level						
High * S1 (high)					.104	1.110
Mod * S1					.155	1.168
Very Low * S1					-.463	.629
High * S2					.612	1.844
Mod * S2					-1.77	.838
Very Low * S2					.433	1.541
High * S3					.465	1.591
Mod * S3					.034	1.034*
Very Low * S3					.034	.602

*signifies ($p < .05$), ** signifies ($p < .01$), *** signifies ($p < .001$)

Table 4.14

Hierarchical logistic regression for lowest SES level predicting high school graduation from control variables and motivation class

	High School Graduation			
	Model 1		Model 2	
Variable	B	Exp(ß)	B	Exp(ß)
STEP 1: Control Variables				
Math Achieve 10th	.060	1.062***	.056	1.058***
Male	-.519	.595***	-.483	.617***
Native American	-.659	.517	-.720	.487
Asian	.263	1.301	.235	1.266
African American	.083	1.087	-.013	.987
Hispanic (no race)	-.185	.831	-.250	.779
Hispanic (race)	-.164	.849	-.228	.796
Mixed	-.526	.591	-.545	.580
Urban	-.182	.834	-.188	.829
Rural	.072	1.074	.083	1.087
STEP 2: Motivation Class				
High Motivation			.377	1.458
Moderate Motivation			.320	1.377**
Very Low Motivation			- .612	.542

*signifies ($p < .05$), ** signifies ($p < .01$), *** signifies ($p < .001$)

Table 4.15

Hierarchical logistic regression predicting postsecondary enrollment from control variables, motivation class, and interaction effects of motivation level and SES levels

	Postsecondary Enrollment					
	Model 1		Model 2		Model 3	
Variable	B	Exp(ß)	B	Exp(ß)	B	Exp(ß)
STEP 1: Control Variables						
Math Achieve 10th	.061	1.063***	.056	1.058***	.056	1.057***
Male	-.351	.704***	-.346	.707***	-.347	.707***
Native American	-.174	.840	-.132	.876	-.152	.859
Asian	.343	1.410**	.316	1.371*	.309	1.362**
African American	-.108	.897	-.180	.835	-.175	.840
Hispanic (no race)	-.167	.845	-.235	.790	-.239	.788*
Hispanic (race)	-.306	.736*	-.380	.684**	-.386	.680***
Mixed	-.320	.726*	-.306	.736	-.305	.737
Urban	.125	1.133	.112	1.119	.112	1.119
Suburban	.055	1.057	.057	1.059	.059	1.061
SESQ1 (high)	.997	2.711***	.960	2.612***	.884	2.419***
SESQ2	.586	1.796***	.582	1.789***	.439	1.551**
SESQ3	.260	1.297**	.251	1.286*	.294	1.341
STEP 2: Motivation Class						
High Motivation			.595	1.814***	.295	1.343
Moderate Motivation			.460	1.583***	.432	1.541
Very Low Motivation			-.215	.806	.375	1.455
STEP 3: Interaction of Motivation and SES level						
High * S1 (high)					.467	1.594
Mod * S1					.061	1.062
Very Low * S1					-.587	.556
High * S2					.806	2.239
Mod * S2					.153	1.166
Very Low * S2					-.669	.512
High * S3					.053	1.055
Mod * S3					-.086	.918
Very Low * S3					-.011	.364

*signifies ($p < .05$), ** signifies ($p < .001$), *** signifies ($p < .001$)

Table 4.16

Hierarchical logistic regression for lowest SES level predicting postsecondary enrollment from control variables and motivation class

	Postsecondary Enrollment			
	Model 1		Model 2	
Variable	B	ß	B	ß
STEP 1: Control Variables				
Math Achieve 10th	.057	1.059***	.054	1.056***
Male	-.436	.646**	-.422	.656**
Native American	.044	1.045	.024	1.025
Asian	.856	2.353***	.839	2.314***
African American	.047	1.048	.014	1.014
Hispanic (no race)	.295	1.343	.259	1.296
Hispanic (race)	-.088	.916	-.134	.875
Mixed	.515	1.673	-.543	1.721
Urban	-.143	.866	-.151	.860
Suburban	-.160	.852	-.175	.839
STEP 2: Motivation Class				
High Motivation			.276	1.318
Moderate Motivation			.434	1.543**
Very Low Motivation			.322	1.379

Table 4.17

Hierarchical logistic regression predicting high postsecondary completion from control variables, motivation class, and interaction effects of motivation level and SES levels

	Postsecondary Completion					
	Model 1		Model 2		Model 3	
Variable	B	Exp(ß)	B	Exp(ß)	B	Exp(ß)
STEP 1: Control Variables						
Math Achieve 10th	.025	1.026***	.024	1.024***	.024	1.024***
Male	-.269	.764***	-.265	.767***	-.264	.768***
Native American	-.504	.604	-.504	.604	-.507	.602
Asian	-.075	.928	-.079	.924	-.082	.921
African American	-.476	.621***	-.497	.609***	-.498	.608***
Hispanic (no race)	-.429	.651***	-.444	.642***	-.449	.638***
Hispanic (race)	-.264	.768**	-.278	.757**	-.281	.755**
Mixed	-.263	.768*	-.260	.771*	-.261	.770*
Urban	.171	1.186*	.166	1.181*	.164	1.178*
Suburban	.112	1.118	.113	1.120	.112	1.119
SESQ1 (high)	.474	1.606***	.463	1.590***	.475	1.608***
SESQ2	.199	1.220**	.196	1.216**	.147	1.158
SESQ3	.081	1.085	.079	1.082	.125	1.113
STEP 2: Motivation Class						
High Motivation			.197	1.217*	.262	1.299
Moderate Motivation			.115	1.122*	.106	1.112
Very Low Motivation			-.170	.844	-.203	.816
STEP 3: Interaction of Motivation and SES level						
High * S1 (high)					-.206	.814
Mod * S1					.016	1.016
Very Low * S1					.932	2.540
High * S2					.129	1.137
Mod * S2					.057	1.059
Very Low * S2					-.099	.906
High * S3					-.077	.926
Mod * S3					-.059	.943
Very Low * S3					-1.172	.310

*signifies ($p < .05$), ** signifies ($p < .001$), *** signifies ($p < .001$)

Table 4.18

Hierarchical logistic regression for lowest SES level predicting postsecondary completion from control variables and motivation class

	Postsecondary Completion			
	Model 1		Model 2	
Variable	B	ß	B	ß
STEP 1: Control Variables				
Math Achieve 10th	.025	1.025***	.023	1.023***
Male	-.397	.673***	-.391	.676***
Native American	-.814	.443	-.811	.445
Asian	.286	1.331	.290	1.336
African American	-.402	.669	-.426	.653
Hispanic (no race)	-.228	.796	-.242	.785
Hispanic (race)	-.128	.880	-.143	.866
Mixed	-.387	.679	-.390	.677
Urban	-.130	.878	-.141	.868
Rural	-.054	.947	-.053	.948
STEP 2: Motivation Class				
High Motivation			.269	1.309
Moderate Motivation			.115	1.122
Very Low Motivation			-.242	.785

Table 4.19

Frequencies of predictors for each dichotomous outcome in logistic regression

Predictor	HS GRAD	PS ENROLL	PS COMPLETE
Native Amer.	81	37	45
Asian	1075	821	827
African Amer.	1168	736	815
Hisp (no race)	655	356	427
Hisp (race)	775	455	500
2+ Race	548	347	370
White	6675	4793	5089
High	1251	1010	1029
Moderate	6090	4509	4706
Very Low	123	42	60
Low	3513	1984	2278
SES1(high)	3296	2829	2821
SES2	2813	2032	2147
SES3	2550	1557	1759
SES4 (low)	2318	1127	1346
Urban	3489	2497	2654
Suburban	5497	3799	4057
Rural	1991	1249	1362
Male	5213	3319	3498
Female	5764	4226	4575

Table 4.20

Frequencies for high school graduation, postsecondary enrollment, and postsecondary completion for each motivation class

	High n = 1249 (11.4%)	*Moderate* n = 6004 (54.7%)	*Low* n = 3593 (32.7%)	*Very Low* n = 135 (1.2%)
HS GRAD				
N = 10,981	n = 1249	n = 6004	n = 3593	n = 135
Yes	1,180 (94.5%)	5,475 (91.2%)	2998 (83.4%)	90 (66.2%)
No	69 (5.5%)	529 (8.8%)	595 (16.6%)	46 (33.8%)
PS ENROLL				
N = 7,572	n = 1035	n = 4427	n = 2059	n = 51
Yes	940 (90.8)	546 (12.3%)	1596 (77.5%)	38 (74.5%)
No	95 (9.2%)	3881 (87.7%)	463 (22.5%)	13 (25.5%)
PS COMPLETE				
N = 9,354	n = 1165	n = 5327	n = 2783	n = 79
Yes	663 (56.9%)	2774 (52.1%)	1275 (45.8%)	33 (41.8%)
No	502 (43.1%)	2553 (47.9%)	1508 (54.2%)	46 (58.2%

CHAPTER 5

DISCUSSION

This study contributed to the extant literature about motivation in high school students by using Expectancy Value Theory and a person oriented approach as the framework to explore how the context of socioeconomic status relates to the formation of motivation profiles and the roles these profiles may have in predicting education trajectories. Five motivation variables were of interest: self-efficacy in math, self-efficacy in English, control expectation (expectations for success in academic learning), action control (self-rated effort and control), and instrumentation motivation, also referred to as utility interest (measure of extrinsic motivation). These variables, per the EVT model, help explain what drives students to achieve in school and choose to continue their education through post-secondary pursuits. Contextual variables such as biological, psychological, and environmental factors, are also considered in the EVT model as they contribute to the formation of ability beliefs, expectancy beliefs, and values that operate on school-related behaviors to produce outcomes (Eccles & Wigfield, 2000; Wang & Degol, 2013). The contextual factors in the EVT model are broad and could easily be extended to include other ecological factors, such as socioeconomic status.

The sample under investigation was a national sample of 10th grade students questioned about their attitudes and experiences in high school to better understand educational opportunities and trajectories (Ingles et al., 2014). These educational experiences are developmentally based, unique to each individual, and a compilation of complex interactions between the person and the environment. It was also assumed that the population used was comprised of subpopulations, thus in keeping with the underlying assumptions of the person-oriented approach (Bergman & Magnusson, 1997).

This study sought to address three research questions: 1) What motivation profiles are evident within a national sample of 10th grade students? 2) How does SES predict motivation class membership?, and 3) Which motivation profiles best predict outcomes (math achievement in 12th grade, high school graduation, postsecondary enrollment immediately after graduation, postsecondary completion) for student at the lowest SES level? This chapter will discuss the findings that answer these questions and their implications as well as the limitations of this study and suggestions for future research.

5.1 WHAT MOTIVATIONAL PROFILES ARE EVIDENT WITHIN A NATIONAL SAMPLE OF 10TH GRADE STUDENTS?

Results of the latent profile analysis yielded four distinct profiles named *high, moderate, low,* and *very low.* Members of the *high* motivation profile endorsed ratings exceeding one standard deviation above the mean on all five motivation measures: math self-efficacy, English self-efficacy, instrumentation motivation (utility value), control expectation, and action control. The *moderate* motivation group had motivation scores just above the mean on all measures, but did not exceed one standard deviation, while the *low* motivation profile had scores that approached but did not exceed one standard deviation below the mean. The fourth, *very low* motivation class was very small and comprised only 1.2% of the population, yet was distinct and reflected extremely low levels of motivation that approached and/or exceeded two standard deviations below the mean.

One striking feature about all of the motivation classes was how "flat" they were, meaning that respondents endorsed motivation items very similarly so that the means on the measures were about the same, regardless of the type of motivation. These finding differed from findings from other studies using person oriented approaches (e.g. cluster analysis or latent class/profile analysis) (Hayenga & Corpus, 2010; Pastor et al, 2007; Ratell et al., 2007; Tuominen-Soini, Salmela-Aro, & Niemivirta, 2011; Viljaranta et al., 2009), all of which found greater heterogeneity in the means across motivation profiles as well as more variability in the relationships between motivation variables.

There are a number of possible explanations for this "flatness" phenomenon. First, developmentally motivation decreases beginning in middle school, which feasibly could extend to high school where student-teacher relationships become even more distant and coursework may be perceived as less relevant (Eccles and Roeser, 2009). The motivation measures were taken in the 10^{th} grade year, sometimes referred to as the "sophomore slump," so students could have conceivably endorsed motivation on all measures similarly because they were disinterested in the survey.

Another explanation is the question placement on the student survey that asked about motivation and attitudes. The question that surveyed students on measures of motivation was number 89 out of 98. Furthermore, this item consisted of 22 sub-questions protracting the length of the questionnaire. Questionnaire length not only affects levels of cooperation by participants, but questions placed toward the end of a survey also tend to have less variability in responses and have shorter responses, if open-ended (Galesic & Bosnjak, 2009). Students may have experienced survey fatigue and higher levels of apathy about their responses given the length of the survey overall, combined with the late placement of this multiple-part question, and thus rated the questions similarly on the 4-point scale.

Lastly, the "flatness" of the profiles might be explained by the number of response items on the rating scale for the motivation questions. With the exception of the study by Hayenga and Corpus (2010), who used a five-point scale, all the other studies noted above based their motivation measures on seven-point Likert scales. Having more options in the scales might have provided higher calibration and variability in responses. Greater number of response options on Likert-type scales are associated with higher reliability and factorial validity, which decrease with fewer response options (Lozano, Garcia-Cueto, & Muniz, 2008). The minimum number or response options recommended is four, with seven being the maximum (Lozano, Garcia-Cueto, & Muniz, 2008). The item-rating scale for the motivation measures on the ELS:2002 student questionnaire were 4-point scales, which could have decreased the variability in responses.

5.2 HOW DOES SES PREDICT MOTIVATION CLASS MEMBERSHIP?

This study was primarily interested in the context of SES level, and although there were findings related to other covariates in this study, SES level remained the focus to the exclusion of other contexts and findings. A pattern of findings from the various analyses completed in this study converged on the same theme: SES level was related to motivation profile assignment. Students from the highest SES level were more likely to be assigned to the *high* and *moderate* motivation profiles, per the covariate analyses that predicted class membership. This finding was echoed in the correlations between SES level and profile status and the chi-square test of independence. The chi-square analyses reflected an inverse relationship between SES level and motivation profile, with students from the highest SES level being less likely to be assigned to the *low* or *very low* motivation profiles, and vice versa. Students from the highest SES level were disproportionately represented in the *high* motivation class, and students from the lowest SES level were disproportionately represented in the *low* and *very low* motivation profiles.

Early research on the topic of motivation and economic status indicated motivation was lower in young children from economically disadvantaged households (Battle & Rotter, 1963; Friedman & Friedman, 1973; Ziegler & Kanzer, 1962), findings that were again supported decades later (Battistich et al., 1995; Brown, 2009; Malakoff, Underhill, & Ziegler, 1998). Bandura and colleagues (2001) demonstrated that SES alone did not directly affect motivation, but rather familial influences such as parents' beliefs and educational and occupational goals for their children indirectly influenced their children's motivations.

5.3 WHICH MOTIVATION PROFILES BEST PREDICT OUTCOMES FOR STUDENTS AT THE LOWEST SES LEVEL?

Motivation profiles, when entered as a block, were statistically significant in virtually all the hierarchical regression models and the omnibus tests for all the equality of means tests also demonstrated that motivation profiles were significant in predicting educational outcomes: higher math achievement in 12th grade, and improved odds for high school graduation, postsecondary enrollment immediately following high school, and postsecondary completion. It is equally important to note that, when entered into the models, the interactions between SES level and motivation profiles were not statistically significant. The combinations of SES level and motivation profiles did not have any effect on math achievement in 12th grade, high school graduation, enrollment in postsecondary education, or postsecondary completion. Rather, SES and motivation profiles acted separately, each having their own effect on outcomes. Although the contribution of motivation profiles was small ($p < .01$) in predicting outcomes, it was statistically significant. In post-hoc analysis, when entered in the first block of the hierarchical regression models, motivation profiles accounted for much more of the variance at $R^2 = .08$, indicating an even higher effect. Entering variables of interest into hierarchical regression models before covariates has been used in other studies to better demonstrate the contribution of those variables, given how variance explained can be impacted depending on order in which variables are entered (Petrocelli, 2003).

Of no surprise, the *high* motivation profile predicted the best outcomes: the largest increases in math achievement, and higher odds for high school graduation, postsecondary enrollment, and postsecondary completion. The *moderate* motivation group also predicted these favorable outcomes, but to a lesser degree. These findings were consistent when the data were aggregated and examined across all four SES levels. When hierarchical regression analyses were performed on the lowest SES level independently, however, a somewhat different picture emerged.

When examined in isolation, for students in the lowest SES quartile, membership in the *high* and *moderate* motivation profiles predicted favorable outcomes, but not consistently, and perhaps not to the same magnitude as when the SES levels were combined. Students in the lowest SES level assigned to the *high* and *moderate* motivation profiles were also predicted to have higher math achievement scores compared to their peers in the *low* motivation profile, however, the magnitude of scores was about half compared to when the data were aggregated. This difference, however, was not tested to determine if was statistically significant. There were differences for high school graduation, postsecondary enrollment, and postsecondary completion as well. Membership in the *high* and *moderate* motivation groups predicted better odds of high school graduation for the data examining all SES levels, but when the lowest SES level was isolated, only the *moderate* motivation profile predicted high school graduation and postsecondary enrollment. Postsecondary completion was not able to be predicted from motivation for the lowest SES level. These results may be less indicative of low SES levels, but rather, related to power issues as a result of smaller motivation profiles sizes given the break-down by SES strata. But lack of power may not be the only issue that confounded outcomes.

The outcomes themselves may confound the findings as they may not be as dependent on motivation as one might intuitively think. For example, high school graduation may not depend on or accurately reflect motivation. Under Every Student Succeeds Act (2015), one measure of school accountability is graduation rate. Schools encourage or even push as many students to graduate as possible, perhaps in spite of students' motivation to do so. This seemed reflected in the graduation rates in this data set: even among students in the low motivation group, 83% graduated from high school, which was higher for higher motivation profiles. Clearly, students graduate from high school at rates that supersede what one would expect given motivation profiles. Indeed, 66% of students in the *very low* motivation profile graduated!

On the other side of the coin, lack of postsecondary enrollment and completion may also not reflect motivation accurately. Approximately 43% of students from the *high* motivation profile and 48% if students from the *moderate* motivation profile did not complete postsecondary degrees. This suggests that other factors, such as economics, may have been far more influential on this outcome than motivation levels and may instead speak to the income-achievement gap, as disproportionately more students from higher income levels complete postsecondary degrees (NCES, 2015). The literature is replete with studies that support the existence of the income-achievement gap (Duncan & Murnane, 2011), yet there have been no known studies that examine if there is an income-motivation gap. This study starts to fill the void in the literature about the relationship between the context of SES level and motivation on the outcomes of high school students.

5.4 IMPLICATIONS

This study made unique contributions to understanding the constellation of motivation profiles, the contexts that relate to these profiles, and how motivation profiles predict educational outcomes: math achievement in 12th grade, high school graduation, postsecondary enrollment, and postsecondary completion. Results from the hierarchical regression and other analyses conducted in this study align with extant research that higher motivation profiles portend more favorable educational outcomes (Hsieh, Sullivan, & Guerra, 2007; Komarraju, Karau, & Schmeck, 2009). However, these outcomes may not be as predictable for highly motivated students who come from economic disadvantage. Although this may be due to limited power, continued investigation into this finding seems warranted. The findings from this study have implication for educators, administrators, and policy-makers alike.

Motivation profiles. Based on the findings from this study using ELS:2002 data, students were found to have similar motivation levels for different types of motivation, which were either *high*, *moderate*, *low*, and very infrequently, *very low*. The motivation variables were highly correlated. Teachers and educators should understand that these motivation profiles are predictive of educational outcomes, with high motivation being optimal, and *moderate* as minimal for predicting positive educational trajectories (Gillet, Morin, & Reeve, 2017).

In addition to SES level, interesting information was garnered from this study about covariates and how they predicted membership into motivation profiles. Males were more likely to be assigned to the high motivation profiles than females, as were African American and Hispanic students, while geographic location had little relationship with motivation profile. These insights may be helpful to educators to know, but ultimately, it does not change the directive – teachers at all levels must build ability beliefs, expectancy beliefs, action control and educational value motivations in students.

Increasing and sustaining healthy levels of motivation is important, especially because motivation tends to decline beginning in middle school and into high school (Eccles & Roeser, 2009), and motivation profiles stabilize during early adolescence (Marcoulides, Gottfried, Gottfried, & Oliver, 2008). Moreover, motivation does not work in isolation, so a change in one type of motivation can negatively or positively affect the motivation profile as a whole, especially when the motivations are highly related (Otis, Grouzet, & Pelletier, 2005). It is therefore incumbent on teachers and administrators to utilize classroom structures and pedagogy that promote adaptive motivation in students (Ames, 1992; Meece, Anderman, & Anderman, 2006).

Motivation and SES relationship. The relationship between motivation and SES has implications at every level. Policy-makers need to explore equitable funding within school systems. Schools from less affluent communities are not afforded the same resources because funding is often localized and based primarily on property taxes, biasing communities with high proportions of home-ownership. Policies-makers at local and state levels need to implement educational programs, such as Pre-K, in high-poverty areas to foster ability beliefs, expectancy beliefs, and values that fuel current and future learning. Additional resources also need to be funneled into high poverty schools to engage students, augment learning, and help channel energies towards productive choices following high school.

Administrators (i.e. principals) should implement policies within their school to foster adaptive and healthy motivation centered around mastery (Anderman, 2011) as well as positive school cultures (Cohen, McCabe, Michelli, & Pickeral, 2009). Additional measures, such as promoting parent-teacher relationships and community supports would be especially important in high poverty schools in order to engage students and their families (Epstein & Sanders, 2006). Efforts to increase academic socialization should be made beginning in the primary school years with the goal of increasing value orientations (Hill, 2001). Professional development may also be necessary to help teachers address the overwhelming demands on them that require skills far beyond teaching skills.

Classroom teachers serving low income schools must be especially vigilant to implement classroom structures and pedagogical methods that promote motivation in students (Ames, 1992; Meece, Anderman, & Anderman, 2006). Knowledge of the relationship between motivation and SES alone may only serve to add to the pressure that these teachers already experience related to achievement, so additional instruction and support may be required. Increasing self-efficacy for learning accompanied self-regulation skills that increase effort and persistence should supersede pressure to succeed on standardized measures of achievement, which may ultimately squelch motivation in the students where motivation may be most fragile.

5.5 LIMITATIONS AND FUTURE RESEARCH

As with all studies, this study was not without its limitations. Most of the limitations of this study were related to the use of secondary data. The use of ELS:2002 data provided many benefits, such as variables of interest, a large sample size, and good power. The limitations were in the pre-determined questions and measurements. The motivation constructs in the ELS:2002 data were well suited for this study, and the coefficients of reliability were strong (.84 – .94), yet the questions may not have been sufficiently different to truly differentiate between motivation types, at least in students' minds which might have contributed to their responding to all the questions similarly. Additionally, the 4-point rating scale may not have been sufficient to capture the variability in motivation, and thus may have contributed to the "flat" profiles, as previously discussed.

Another limitation of the secondary data was there were no follow-up measures on motivation at 12th grade. Measures taken in 12th grade might have better reflected students' motivation profiles measured in 10th grade after maturation occurred and important life-choices became more imminent. Although previous research has shown that motivation profiles stabilize around middle school (Gillet, Morin, & Reeve, 2017; Marcoulides et al., 2008), little work has explored whether motivation remains stable in late adolescence. A follow-up of motivation measures would have allowed addition studies using transitional analysis, which would have provided interesting insight.

Lastly, the most challenging aspect of the secondary data was related to accounting for the complex sample design and applying weights. Even one of the more sophisticated statistical software packages (i.e. Mplus) was unable to accommodate all the weights required for the analyses. Specifically, neither the panel weight nor the PSU could be applied to the distal outcome measures in Mplus. In fact, the weight prohibited the use of the 3-step method, which is the preferred method for examining distal outcomes. There was also a small problem when transitioning to from Mplus to SPSS and this transition between software packages was not completely seamless. The sample sizes aligned for analyses in SPSS only when the weight was off, which created slight shifts in the distribution of cases in the motivation class sizes. Overall, the benefits outweighed the limitations and the ELS:2002 data provide ample opportunity for future research.

5.6 FUTURE RESEARCH

A different type of analysis, such as factor mixture modeling, might allow the researcher to gain a deeper understanding of the relationship between SES level and motivation profiles, and should be considered for the future. Factor mixture modeling is a hybrid of latent class analysis and factor analysis, which allows assumptions to be relaxed and allows correlations between indicators on measures that are also related to a latent variable thus allowing conditional dependence in the analysis (Morin, Morizot, Boudrais, & Madore, 2011).

Exploratory analyses on this same data set (ELS:2002) were performed completing LPA at each SES level. Preliminary analyses found the same types of profiles, *high*, *moderate*, *low*, and *very low* (for the lowest SES level only), but the small class sizes in some of the profiles may have been too small to predict outcomes. Additional exploration, such as regression analysis parsing out motivation variables, may yield a deeper understanding as to how motivations operate differently on each SES level.

The goal of this line of research is to better understand the relationship between ecological contexts on motivation in students. This will allow researchers to target interventions to improve, not just motivation, but ultimately improve outcomes for all students. More importantly, the goal is to increase equity to those students who do not have the same level of educational and social capital others have based solely on the economic status of their families.

5.7 CONCLUSION

This study made important contributions to the literature in a number of ways. First, this study added to the extant research using Expectancy Value Theory (Wigfield & Eccles, 2000) and supported that high school students with high self-efficacy in math and English, expectations for success, who exert effort and persistence, and hold utility value, not only graduate high school at higher rates, but also go on to enroll in postsecondary education immediately following high school and earn postsecondary degrees at high rates than students with lower motivation profiles. Furthermore, by exploring the relationship of SES and motivation profiles, this study extended the concept that contexts may be related to the formation of motivations and values, also included in the EVT model, but studied to a lesser degree (Wang & Degol, 2013).

The methodological approach, latent profile analysis, also contributed to the literature in ways that a variable approach would not allow. First, it demonstrated how tightly different motivation constructs cluster together to form profiles that predicted benchmark educational outcomes. Additionally, it allowed for exploration as to how covariates relate to these profiles, and provided important insights about the relationship between SES and motivation. LPA also demonstrated that while there is a pattern of relationships, there is also heterogeneity of motivation profiles across SES levels. SES levels do not predetermine motivation profiles and underscores the importance of considering a multitude of factors that contribute to it.

In light of the income-achievement gap that is plaguing our nation, this study opens the door to a line of research to explore the possibility of an income-motivation gap, which has implications for the classroom and educational policies. This study also sets a path for future research toward improving educational outcomes in our less advantaged students.

REFERENCES

American Council on the Teaching of Foreign Languages, (2012). ACTFL Proficiency Guidelines: 2012. Retrieved from : https://www.actfl.org/sites/default/files/pdfs/public/ACTFLProficiencyGuidelines2012_FINAL.pdf

American Psychological Association (2017). Ethnic and racial minorities & socioeconomicstatus. Retrieved from: http://www.apa.org/pi/ses/resources/publications/minorities.aspx on October 10, 2017.

Ames, C. (1992). Classrooms: Goals, structures, and student motivation. *Journal of Educational Psychology*, *84*, 261–271.

Anderman, E. M. (2011). Adolescence. In K. R. Harris, S. Graham, & T. Urdan (Eds.), *APA Educational Psychology Handbook: Vol. 3* (pp. 43-61).

Andersen, L. & Ward, T. J. (2013). Expectancy-Value Models for the STEM Persistence Plans of Ninth-Grade, High-Ability Students: A Comparison Between Black, Hispanic, and White Students. *Science Education*, *98*, 216-242. doi:10.1002/sce.21092

Asparouhov, T. & Muthén, B. (2007). Wald test of mean equality for potential latent class predictors in mixture modeling. Retrieved from : https://www.statmodel.com/download/MeanTest1.pdf

Asparouhov, T. & Muthén, B.O. (2014). Auxiliary variables in mixture modeling: 3-step approaches using Mplus. Mplus Web Notes: No 15.

Bandura, A. (1977). Self-efficacy: toward a unifying theory of behavioral change. *PsychologicalReview*, *84*, 191-215.

Bandura, A. (1993). Perceived self-efficacy in cognitive development and functioning. *Educational Psychologist*, *28*(2), 117-148.

Bandura, A. (1997). *Self-efficacy: The exercise of control.* New York, NY: W.H. Freeman.

Bandura, A., Barbaranelli, C., Caprara, G. V., & Pastorelli, C. (2001). Self-efficacy beliefs as shapers of children's aspirations and career trajectories. *Child Development*, *72*, 187-206.

Battistich, V., Solomon, D., Kim, D. I., Watson, M., & Schaps, E. (1995). Schools as communities, poverty levels of student populations, and students' attitudes, motives, and performance: A multilevel analysis. *American Educational Research Journal*, *32*, 627- 658.

Battle, A. & Wigfield, A. (2003). College women's value orientations toward family, career, and graduate school. *Journal of Vocational Behavior, 62,* 56-75. doi:10.1016/S00018791(02)00037-4

Battle, E. S. & Rotter, J. B. (1963). Children's feelings of personal control as related to social class and ethnic group. *Journal of Personality*, *31*, 482-490

Belmechri, F. & Hummel, K. (1998). Orientations and motivation in the acquisition of English as a second language among high school students in Quebec City. *Language Learning, 48,* 219-244.

Benbow, C. P., Lubinski, D., Shea, D. L., & Eftekhari-Sanjani, H. (2000). Sex differences in mathematical reasoning ability at age 13: Their status 20 years later. *Psychological Science*, *11*, 474-480.

Bergman, L. R. & Magnusson, D. (1997). A person-oriented approach in research on developmental psychopathology. *Development and Psychology, 9,* 291-319.

Bergman, L. R. & Trost, K. (2006). The person-oriented versus the variable-oriented approach: Are they complementary, opposites, ore exploring different worlds? *Merrill-Palmer Quarterly, 52,* 601-632.

Betz, N. E. & Hackett, G. (1983). The relationship of mathematics self-efficacy expectations to the selection of a science-based college majors. *Journal of Vocational Behavior, 23* 329-345.

Bong, M. (2001). Role of self-efficacy and task-value in predicting college students' course performance and future enrollment intentions. *Contemporary Educational Psychology*, *26*, 553-570.

Brody, G. H., Stoneman, Z., & Flor, D. (1995). Linking family processes and academic competence among rural African American youths. *Journal of Marriage and the Family*, 567-579.

Brody, G. H., Stoneman, Z., Flor, D., McCrary, C., Hastings, L., & Conyers, O. (1994). Financial resources, parental functioning, parent co-caregiving, and early adolescent competence in rural two-family African-American families. *Child Development, 65,* 590-605.

Brooks-Gunn, J. & Duncan, G. T. (1997). The effects of poverty on children. *The Future of Children, 7,* 55-71.

Brown, E. D. (2009). Persistence in the face of academic challenge for economically disadvantaged children. *Journal of Early Childhood Research*, *7*, 173-184. Malakoff, M. E., Underhill, J. M., & Zigler, E. (1998). Influence of inner-city environment and Head Start experience on effectance motivation. *American Journal of Orthopsychiatry, 68*, 630-638.

Burdic-Will, J., Ludwig, J., Raudensbush, S. W., Sampson, R. J., Sanboumastu, L., & Sharkey, P, (2012). Converging evidence of neighborhood effects on children’t test scores: An experimental, quasi-experimental, and observational comparison. In G. J. Duncan & R. J. Murnane (Eds.), *Whither Opportunity?* (pp. 255-276). New York, NY: Russell Sage Foundation.

Career Addict (2016, January 13). The importance of good writing skills in the workplace. Retrieved from: https://www.careeraddict.com/the-importance-of-good-writing-skills-in-the-workplace

Carlson, B. L., & Cohen, S. B. (1993). An evaluation of the use of personal computers for variance estimation with complex survey data. *Journal of Official Statistics, 9*(4), 795. Retrieved from https://librarylink.uncc.edu/login?url=https://search-proquest-com.librarylink.uncc.edu/docview/1266817299?accountid=14605

Chapmans, C., Laird, J., Ifill, N., Kewal Ramani, A. (2011). Trends in High School Dropout and Completion Rates in the United States: 1972-2009 Compendium Report. *National Center for Educational Statistics*. Retrieved from: https://nces.ed.gov/pubs2012/2012006.pdf

Christle, C. A. & Yell, M. L. (2008). Preventing youth incarceration through reading remediation: Issues and solutions. *Reading & Writing Quarterly*, *24*, 148-176.

Clark, S. L., & Muthén, B. (2009). Relating latent class analysis results to variables not included in the analysis. Retrieved from http://www.statmodel.com/download/relatinglca.pdf

Cohen, J., McCabe, L., Michelli, N. M., & Pickeral, T. (2009). School climate: Research, policy, practice, and teacher education. *Teachers college record*, *111*(1), 180-213.

Collins, L. M. & Lanza, S. T. (2010). *Latent class and latent transitional analysis: With applications in the social, behavioral, and health sciences.* Hoboken, NJ: John Wiley & Sons, Inc.

Conger, R. D., & Donnellan, M. B. (2007). An interactionist perspective on the socioeconomiccontext of human development. *Annual Review of Psychology*, *58*, 175-199.

Conger, R. D., Conger, K. J., Elder, G. H., Lorenz, F. O., Simons, R. L., & Whitbeck, L. B. (1992). A family process model of economic hardship and adjustment of early adolescent boys. *Child Development*, *63*, 526-541.

Conley, A. M. (2012). Patterns of motivation beliefs: Combining achievement goal and expectancy-value perspectives. *Journal of Educational Psychology*, *104*, 32-47.

Cox, A. E. & Whaley, D. E. (2004). The influence of task value, expectancies for success, and identity on athletes' achievement behaviors. *Journal of Applied Sport Psychology*, *16*, 103-117.

Cox, B. G. (1980). The weighted sequential hot deck imputation procedure. In *Proceedings of the American Statistical Association, Section on Survey Research Methods*, 721-726.

Csizer, K. & Dornyei, Z. (2005). Language learners' motivational profiles and their motivated learning behavior. *Language Learning, 55,* 613-659.

Davis-Kean, P. E. (2005). The influence of parent education and family income on child achievement: the indirect role of parental expectations and the home environment. *Journal of Family Psychology*, *19*, 294-304. doi: 10.1037/0893 3200.19.2.294

DiStefano, C. (2012). Cluster analysis and latent class clustering techniques. In B. Laursen, T. D. Little, Y N. A. Card (Eds.). *Handbook of Developmental Research Methods* (pp. 645-686). New York, NY: Guildford Press.

DiStefano, C. & Kamphaus, R. W. (2006). Investigating subtypes of child development: A comparison of cluster analysis and latent class analysis in typology creation. *Educational and Psychological Measurement, 66,* 778-794. doi: 10.1177/0013164405284033
doi: 10.1037/a0026042

Duffy, R. D. & Sedlacek, W. E. (2007). The work values of first-year college students: Exploring group differences. *The Career Development Quarterly, 55,* 359-364.

Duncan, G. J. & Magnuson, K. (2011). The Nature and Impact of Early Achievement Skills, Attention Skills, and Behavior Problems in G. J. Duncan & R. J. Murnane (Eds.), *Whither Opportunity?* (pp. 47-70). New York, NY: Russell Sage Foundation.

Duncan, G. J. and Murdane, R. J. (Ed.). (2011). *Whither Opportunity*. New York, NY: Russell Sage Foundation.

Duncan, G. J., Brooks-Gunn, J., & Klebanov, P. K. (1994). Economic deprivation and early childhood development. *Child Development, 65,* 296-318.

Duncan, G. T. & Brooks-Gunn, J. (2000). Family poverty, welfare reform, and child development. *Child Development, 71,* 188-196.

Durik, A. M., Vida, M., & Eccles, J. S. (2006). Task values and ability beliefs as predictors of high school literacy choices: A developmental analysis. *Journal of Educational Psychology, 98*, 382-393. doi: 10.1037/0022-0663.98.2.382

Dweck, C. S. (1986). Motivational processes affecting learning. *American Psychologist, 41,* 1040-1048.

Dweck, C. S. & Molden, D. C. (2005). Self-theories: Their impact on competence motivation and acquisition. In A. J. Elliot, & C. S. Dweck (Eds.), *Handbook of Competence and Motivation* (pp. 122–140). New York, NY: Guildford Press.

Dweck, C. S., Chiu, C. Y., & Hong, Y. Y. (1995). Implicit theories and their role in judgments and reactions: A word from two perspectives. *Psychological inquiry*, *6*(4), 267-285.

Eccles, J. S. & Wigfield, A. (1995). In the mind of the achiever: The structure of adolescents' academic achievement related beliefs and self-perceptions. *Personality and Social Psychology Bulletin, 21,* 215-225.

Eccles, J. S., & Midgley, C. (1989). Stage/environment fit: Developmentally appropriate classrooms for early adolescents. In R. Ames & C. Ames (Eds.), *Research on Motivation in Education*, vol. *3* (pp. 139–181). New York, NY: Academic Press.

Eccles, J. S., & Roeser, R. W. (2009). Schools, academic motivation, and stage environment fit. In Edited by R. M. Lerner & L. Steinberg (Eds.). *Handbook of Adolescent Psychology* (pp. 404-434.) Hoboken, NJ: Wiley.

Eccles, J. S., Adler, T. F., Futterman, R., Goff, S. B., Kaczala, C. M., Meece, J., & Midgley, C. (1983). Expectancies, values and academic behaviors. In J. T. Spence (Ed.), *Achievement and Achievement Motives* (pp. 75–146). San Francisco, CA: Freeman.

Eccles, J. S., Wigfield, A., Harold, R., & Blumenfeld, P. B. (1993). Age and gender differences in children's self-and task perceptions during elementary school. *Child Development, 64,* 830-847.

Eccles, J. S., Wong, C. A., & Peck, S. C. (2006). Ethnicity as a social context for the development of African-American adolescents. *Journal of School Psychology, 44,* 401-426. doi: 10.1016/j.jsp.2006.04.001

Epstein, J. L., & Sanders, M. G. (2006). Prospects for change: Preparing educators for school, family, and community partnerships. *Peabody journal of Education*, *81*(2), 81-120.

Evans, G. W. (2004). The environment on childhood poverty. *American Psychologist, 59,* 77 92.

Farkas, G. (2011). Middle and High School Skills, Behaviors, Attitudes, and Curriculum Enrollment, and Their Consequences in G. J. Duncan & R. J. Murnane (Eds.), *Whither Opportunity?* (pp. 71-90). New York, NY: Russel Sage Foundation.

Findley, M. J. & Cooper, H. M. (1983). Locus of control and academic achievement: A literature review. *Journal of Personality and Social Psychology*, *44*, 419-427. doi: 10. 1037/00223514.44.2.419

Finn, J. D. & Rock, D. A. (1997). Academic success among students at risk for school failure. *Journal of Applied Psychology, 82,* 221-234.

Ford, D. H. & Lerner, R. M. (1992). *Developmental systems theory: An integrative approach*. Thousand Oaks, CA: Sage Publications, Inc.

Fredricks, J. A. & Eccles, J. S. (2005). Family socialization, gender, and sport motivation and involvement. *Journal of Sport and Exercise Psychology*, *27*, 3-31.

Friedman, P. & Friedman, H. (1973). Frequency and types of teacher reinforcement given to lower and middle class students. Paper presented at the American Educational Research Association annual meeting, New Orleans, LA., February 1973.

Gao, Z. (2008). College students' motivation toward weight training: A combined perspective. *Journal of Sport Behavior*, *31,* 22-43. Guan, J., Xiang, P.,

Gardner, R. C., & Lambert, W. E. (1972). *Attitudes and motivation in second-language learning.* Rowley, MA: Newbury House Publishers.

Geiser, C. (2010). *Data Analysis with Mplus.* New York, NY: Guilford Press.

Gillet, N., Morin, A. J., & Reeve, J. (2017). Stability, change, and implications of students' motivation profiles: A latent transition analysis. *Contemporary Educational Psychology*, *51*, 222-239.

Goodenow, C. & Grady, K. E. (1993). The relationship of school belonging and friends' values to academic motivation among urban adolescent students. *The Journal of Experimental Education, 62,* 60-71.

Guthrie, J. T., Coddington, C. S., & Wigfield, A. (2009). Profiles of reading motivation among African American and Caucasian students. *Journal of Literacy Research*, *41*, 317-353. doi: 10.1080/10862960903129196

Gutman, L. M. (2006). How student and parent goal orientations and classroom goal \ structures influence the math achievement of African Americans during the high school transition. *Contemporary Educational Psychology*, *31*, 44-63.

Hackett, G. (1985). Role of mathematics self-efficacy in the choice of math-related majors of college women and men: A path analysis. *Journal of Counseling Psychology, 32*, 47-56.

Hackett, G., & Betz, N. E. (1989). An exploration of the mathematics self-efficacy/mathematics performance correspondence. *Journal for Research in Mathematics Education*, 261-273.

Hardré, P. L. & Reeve, J. (2003). A motivational model of rural students' intentions to persist in, versus drop out of, high school. *Journal of Educational Psychology, 95,* 347-356. doi: 10.1037/0022-0663.95.2.347

Hayenga, A. O., & Corpus, J. H. (2010). Profiles of intrinsic and extrinsic motivations: A person centered approach to motivation and achievement in middle school. *Motivation and Emotion*, *34*, 371-383. doi: 10.1007/s11031-010-9181-x

Hill, N. E. (2001). Parenting and academic socialization as they relate to school readiness: The roles of ethnicity and family income. *Journal of Educational Psychology*, *93*, 686.
Hsieh, P., Sullivan, J. R., & Guerra, N. S. (2007). A closer look at college students: Self-efficacy and goal orientation. *Journal of Advanced Academics*, *18*(3), 454-476.
Ing, M., & Nylund-Gibson, K. (2013). Linking early science and mathematics attitudes to long-term science, technology, engineering, and mathematics career attainment: Latent class analysis with proximal and distal outcomes. *Educational Research and Evaluation*, *19*, 510-524.
Ingels, S. J., Pratt, D. J., Alexander, C. P., Jewell, D. M., Lauff, E., Mattox, T. L., & Wilson, D., (2014). Education Longitudinal Study of 2002 (ELS: 2002) Third Follow-up Data File Documentation. NCES 2014-364. National Center for Education Statistics.
Ingels, S.J., Pratt, D.J., Rogers, J.E., Siegel, P.H., and Stutts, E.S. (2005). Education Longitudinal Study of 2002: Base-Year to First Follow-up Data File Documentation (NCES 2006–344). U.S. Department of Education. Washington, DC: National Center for Education Statistics.
Ingels, S.J., Pratt, D.J., Wilson, D., Burns, L.J., Currivan, D., Rogers, J.E., & Hubbard-Bednasz, S. (2007). Education Longitudinal Study of 2002: Base-Year to Second Follow up Data File Documentation (NCES 2008-347). U.S. Department of Education. Washington, DC: National Center for Education Statistics.
Ingles, S. J., Pratt, D. J., Rogers, J. E., Siegel, P. H., & Stutts, E. S. (2004). Base Year Data File User's Manual. (NCES 2004-405). U.S. Department of Education. Washington, DC: National Center for Education Statistics.
Irvin, M. J. (2012). Role of student engagement in the resilience of African American adolescents from low-income rural communities. *Psychology in the Schools, 49,* 179-193. doi: 10.1002/pits.20626
Isenberg, E., Max, J., Gleason, P., Johnson, M., Deutsch, J., & Hansen, M. (2016). Do Low-Income Students Have Equal Access to Effective Teachers? Evidence from 26 Districts (NCEE 2017-4007). Washington, DC: National Center for Education Evaluation and Regional Assistance, Institute of Education Sciences, U.S. Department of Education. Retrieved from: https://ies.ed.gov/ncee/pubs/20174008/pdf/20174007.pdf
Jimerson, S. R., Campos, E., & Greif, J. L. (2003). Toward an understanding of definitions andmeasures of school engagement and related terms. *The California School Psychologist, 8,* 7-27.
Kalechstein, A. D., & Nowicki Jr, S. (1997). A meta-analytic examination of the relationship between control expectancies and academic achievement: An 11-year follow-up to Findley and Cooper. *Genetic, Social, and General Psychology Monographs*, *123*, 27-57.
Komarraju, M., Karau, S. J., & Schmeck, R. R. (2009). Role of the Big Five personality traits in predicting college students' academic motivation and achievement. *Learning and individual differences*, *19*(1), 47-52.
Kozol, J. (2005). *The Shame of the Nation*. New York, NY: Crown Publishers.

Kuhl, J. (1984). Volitional aspects of achievement motivation and learned helplessness: Toward a comprehensive theory of action control. In *Progress in Experimental Personality Research*, *13,* 99-171.

Laerd Statistics (2015). Statistical tutorials and software guides. Retrieved from https://statistics.laerd.com/

Lanza, S. T., Tan, X., & Bray, B. C. (2013). Latent class analysis with distal outcomes: A flexible model-based approach. *Structural equation modeling: a multidisciplinary journal*, *20*, 1-26.

Lee, V. E., Smith, J. B., & Croninger, R. G. (1997). How high school organization influences the equitable distribution of learning in mathematics and science. *Sociology of Education*, *2*, 128-150. doi: 10.2307/2673160

Lent, R. W., Lopez, F. G., & Bieschke, K. J. (1991). Mathematics self-efficacy: Sources and relation to science-based career choice. *Journal of Counseling Psychology*, *38*, 424-430.

Little, T. D., Oettingen, G., Stetsenko, A., & Baltes, P. B. (1995). Children's action-control beliefs about school performance: How do American children compare with German and Russian children? *Journal of Personality and Social Psychology, 69,* 686-700.

Lopez, D. F. (1999). Self-regulated learning: The impact of action-control beliefs and academic goals on achievement-related outcomes. *Learning and Individual Differences, 11,* 302-319.

Lozano, L. M., García-Cueto, E., & Muñiz, J. (2008). Effect of the number of response categories on the reliability and validity of rating scales. *Methodology: European Journal of Research Methods for the Behavioral and Social Sciences*, *4*(2), 73.

Lubinski, D., Webb, R. M., Morelock, M. J., & Benbow, C. P. (2001). Top 1 in 10,000: a 10 year follow-up of the profoundly gifted. *Journal of Applied Psychology*, *86*, 718-729. doi: 10.1037//0021-9010.86.4.718

Maaz, K., Trautwein, U., Lüdtke, O., & Baumert, J. (2008). Educational transitions and differential learning environments: How explicit between-school tracking contributes to social inequality in educational outcomes. *Child Development Perspectives*, *2*, 99-106.

Maddux, J. E., Sherer, M., & Rogers, R. W. (1982). Self-efficacy expectancy and outcome expectancy: Their relationship and their effects on behavioral intentions. *Cognitive Therapy and Research*, *6*, 207-211.

Maehr, M. L., & Meyer, H. A. (1997). Understanding motivation and schooling: Where we've been, where we are, and where we need to go. *Educational Psychology Review*, *9*, 371 - 409.

Marcoulides, G. A., Gottfried, A. E., & Gottfried, A. W., & Oliver, P. H. (2008) A latent transition analysis of academic intrinsic motivation from childhood through adolescence, *Educational Research and Evaluation, 14*, 411 427, DOI: 10.1080/13803610802337665

Margolis, H. & McCabe, P. P. (2006). Improving self-efficacy and motivation: What to do, what to say. *Intervention in school and clinic*, *41*, 218-227.

McBride,R., & Bruene, A. (2006). Achievement goals, social goals, and students' reported persistence and effort in high school physical education. *Journal of Teaching in Physical Education*, *25*, 58-74.

McLoyd, V. C. (1990). The impact of economic hardship on Black families and children: Psychological distress, parenting, and socioemotional development. *Child Development, 61,* 311-346.
McLoyd, V. C. (1998). Socioeconomic disadvantage and child development. *American Psychologist, 53,* 185-204.
Meece, J. L., Anderman, E. M., & Anderman, L. H. (2006). Classroom goal structure, student motivation, and academic achievement. *Annual Review of Psychology*, *57*, 487-503.
Meece, J. L., Wigfield, A., & Eccles, J. S. (1990). Predictors of math anxiety and its influence on young adolescents' course enrollment intentions and performance in mathematics. *Journal of Educational Psychology*, *82*, 60-70.
Morin, A. J. S., Morizot, J., Boudrais, J-S, and Madore, I. (2011). A multifoci person-centered perspective on workplace affective commitment: A latent profile/factor mixture analysis. *Organizational Research Methods, 14,* 58-90. doi: 10.1177/1094428109356476
Multon, K. D., Brown, S. D., & Lent, R. W. (1991). Relation of self-efficacy beliefs to academic outcomes: A meta analytic investigation. *Journal of Counseling Psychology, 38*, 30-38. http://dx.doi.org/10.1037/0022-0167.38.1.30
Muthén, B. & Muthén, L. K. (2000). Integrating person-centered and variable-centered analysis: Growth mixture modeling with latent trajectory classes. *Alcoholism: Clinical and Experimental Research, 24,* 882-891.
Muthen, L. K. (2012, July 17). Mplus Discussion. Retrieved from http://www.statmodel.com/discussion/messages/22/4448.html
Muthén, L.K. and Muthén, B.O. (1998-2017). Mplus User's Guide. Eight Edition. Los Angeles, CA: Muthén & Muthén.
National Center for Education Statistics (NCES). (2017). Distance Learning Dataset Training. Retrieved from https://nces.ed.gov/training/datauser/
National Center for Educational Statistics (2015, May). Postsecondary attainment: Differences by socioeconomic status. Retrieved from https://nces.ed.gov/programs/coe/indicator_tva.asp.
National Center for Educational Statistics (2017, March). Immediate college enrollment rate. Retrieved from https://nces.ed.gov/programs/coe/indicator_cpa.asp
National Center for Educational Statistics (2017). Distance Learning Dataset Training. ELS:2002 Sample Design, Weights, Variance, and Missing Data. Retrieved from https://nces.ed.gov/training/datauser/ELS_04.html
National Center for Educational Statistics (2018). Trends in high school dropout and completion rates in the United States. Retrieved from https://nces.ed.gov/programs/dropout/ind_sp.asp
Nylund-Gibson, K., Grimm, R., Quirk, M., & Furlong, M. (2014). Latent transition mixture model using the three-step specification. *Structural Equation Modeling: A Multidisciplinary Journal, 21,* 439-454. doi: 10.1080/10705511.2014.915375
Nylund-Gibson, K. L., & Masyn, K. E. (2011, April). Including auxiliary variables in latent class analysis. In *Annual meeting of the Western Psychological Association*, Los Angeles, CA.

Oakes, J. (1990). Multiplying inequalities: The effects of race, social class, and tracking on opportunities to learn mathematics and science. Retrieved from: https://eric.ed.gov/?id=ED329615

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

Otis, N., Grouzet, F. E., & Pelletier, L. G. (2005). Latent motivational change in an academic setting: A 3-year longitudinal study. *Journal of Educational Psychology, 97*, 170-183. doi: 10.1037/0022-0663.97.2.170

Pajares, F. & Johnson, M. J. (1996). Self-efficacy beliefs and the writing performance of entering high school students. *Psychology in the Schools, 33,* 163-175.

Pajares, F. & Miller, M. D. (1994). Role of self-efficacy and self-concept beliefs in mathematical problem solving: A path analysis. *Journal of Educational Psychology*, *86*, 193-203.

Pajares, F. & Schunk, D. (2001). The development of academic self-efficacy. *Development of achievement motivation. United States*, *7*. https://www.uky.edu/~eushe2/Pajares/SchunkPajares2001.PDF

Parker, P. D., Marsh, H. W., Ciarrochi, J., Marshall, S., & Abduljabbar, A. S. (2014). *Educational Psychology, 34*, 29-48. doi: 10.1080/01443410.2013.797339

Pastor, D. A., Barron, K. E., Miller, B. J., & Davis, S. L. (2007). A latent profile analysis of college students' achievement goal orientation. *Contemporary Educational Psychology, 32,* 8-47.

Petrocelli, J. V. (2003). Hierarchical multiple regression in counseling research: Common problems and possible remedies. *Measurement and Evaluation in Counseling and Development*, *36*, 9-22.

Pietsch, J., Walker, R., & Chapman, E. (2003). The relationship among self-concept, self-efficacy, and performance in mathematics during secondary school. *Journal of Educational Psychology, 95,* 589-603. doi: 10.1037/0022-0663.95.3.589

Pintrich, P. R. & Schunk, D. H. (2002). *Motivation in education: Theory, research, and application* (2nd Ed.) Merrill Prentice Hall, Columbus, OH.

Pong, S. L. & Ju, D. B. (2000). The effects of change in family structure and income on dropping out of middle and high school. *Journal of Family Issues*, *21*, 147-169.

Quirk, M., Nylund-Gibson, K., & Furlong, M. (2013). Exploring patterns of Latino/a children's school readiness at kindergarten entry and their relations with Grade 2 achievement. *Early Childhood Research Quarterly, 18*, 437-449. doi: 10.1016/j.ecresq.2012.11.002

Ratelle, C. F., Guay, F., Vallerand, R. J., Larose, S., & Senécal, C. (2007). Autonomous, controlled, and amotivated types of academic motivation: A person-oriented analysis. *Journal of educational psychology*, *99*, 734-746. doi: 10.1037/t01069-000

Reardon, S. F. (2011). The widening academic achievement gap between the rich and the poor: New evidence and possible explanations. In G. J. Duncan & R. J. Murnane (Eds.), *Whither Opportunity?* (pp. 91-116). New York, NY: Russell Sage Foundation.

Reardon, S. F. (2013). The widening income achievement gap. *Educational Leadership*, 11-16.

Reddick, R. J., Welton, A. D., Alsandor, D. J., Denyszyn, J. L., & Platt, C. S. (2011). Stories of success: High minority, high poverty public school graduate narratives on accessing higher education. *Journal of Advanced Academics*, *22*, 594-618.

Rist, R. (2000). HER classic reprint-student social class and teacher expectations: the self-fulfilling prophecy in ghetto education. *Harvard Educational Review*, *70*, 257 302.

Ritchie, S. J. & Bates, T. C. (2013). Enduring links from childhood mathematics and reading achievement to adult socioeconomic status. *Psychological Science*, *24*, 1301-1308.

Rosentlutl, R. & Jacobson, L. F. (2000). Teacher expectations for the disadvantaged. *Psychology of Education: Schools, teachers and parents*, *1*, 331.

Ruble, D. N., Martin, C. L., & Berenbaum, S. A. (1998). Gender development. *Handbook of Child Psychology*. doi: 10.1002/9780470147658.chpsy0314

Rumberger, R. W. (2001). Why students drop out of school and what can be done. Paper prepared for the Conference, "Dropouts in America: How Severe is the Problem? What Do We Know about Intervention and Prevention?" Harvard University, January 13, 2001. 1-52.

Ryan, R. M. & Deci, E. L. (2002). Overview of self-determination theory: An organismic dialectical perspective. In E. L. Deci & R. M. Ryan (Eds.), *Handbook of self-determination research* (pp. 3–33). Rochester, NY: University of Rochester.

Schneider, B., Swanson, C. B., & Riegle-Crumb, C. (1997). Opportunities for learning: Course sequences and positional advantages. *Social Psychology of Education*, *2*, 25-53.

Schunk, D. H. (1991). Self-efficacy and academic motivation. *Educational Psychologist*, *26*, 207-231.

Senko, C., Hulleman, C. S., & Harackiewicz, J. M. (2011). Achievement goal theory at the crossroads: Old controversies, current challenges, and new directions. *Educational Psychologist*, *46*, 26-47.

Shell, D. F., Colvin, C., & Bruning, R. H. (1995). Self-efficacy, attribution, and outcome expectancy mechanisms in reading and writing achievement: Grade-level and achievement-level differences. *Journal of Educational Psychology, 3,* 386-398.

Shell, D. F., Murphy, C. C., & Bruning, R. H. (1989). Self-efficacy and outcome expectancy mechanisms in reading and writing achievement. *Journal of Educational Psychology*, *81*, 91-100. doi.org.librarylink.uncc.edu/10.1037/0022 0663.81.1.91

Simpkins, S. D., Davis-Kean, P. E., & Eccles, J. S. (2006). Math and science motivation: A longitudinal examination of the links between choices and beliefs. *Developmental Psychology, 42*, 70-83. doi: 10.1037/0012-1649.42.1.70

Sirin, S. R. (2005). Socioeconomic status and academic achievement: A meta-analytic review of research. *Review of Educational Research, 75,* 417- 453.

Skinner, E. A., Chapman, M., & Baltes, P. B. (1988). Children's beliefs about control, means ends, and agency: Developmental differences during middle childhood. *International Journal of Behavioral Development, 11,* 369-388.

Skinner, E. A., Wellborn, J. G., & Connell, J. P. (1990). What it takes to do well in school and whether I've got it: A process model of perceived control and children's engagement and achievement in school. *Journal of Educational Psychology, 82,* 22-32. doi: 10.1037//0022-0663.82.1.22

Steinmayr, R. & Spinath, B. (2009). The importance of motivation as a predictor of school achievement. *Learning and Individual Differences*, *19*, 80-90.

Sterba, S. K. & Bauer, D. J. (2010). Matching method with theory in person-oriented developmental psychopathology research. *Development and Psychopathology, 22,* 239- 254. doi: 10.1017/S0954579410000015

Stevens, T., Olivarez, A., & Hamman, D. (2006). The role of cognition, motivation, and emotion in explaining the mathematics achievement gap between Hispanic and White students. *Hispanic Journal of Behavioral Sciences, 28,* 161-186.

Stewart, E. B. (2007). Individual and school structural effects on African American high school students' academic achievement. *The High School Journal, 91,* 16-34.

Stewart, E. B. (2008). School structural characteristics, student effort, peer associations, and parental involvement. *Education and Urban Society, 40,* 179-204.

Stipek, D. J., & Ryan, R. H. (1997). Economically disadvantaged preschoolers: Ready to learn but further to go. *Developmental Psychology*, 33, 711-723.

Tierny, W. G. (2015). Education's role in the elimination of poverty in the twenty-first century. In W. G. Tierny (Ed.), *Rethinking Education and Poverty* (pp. 1-17). Baltimore, MD: Johns Hopkins University Press.

Tuominen-Soini, H., Salmela-Aro, K., & Niemivirta, M. (2011). Stability and change in achievement goal orientations: A person-centered approach. *Contemporary Educational Psychology*, *36*, 82-100.

Urdan, T. C. & Maehr, M. L. (1995). Beyond a two-goal theory of motivation and achievement: A case for social goals. *Review of Educational Research, 65,* 213 243.

Vermunt, J. K. (2010). Latent class modeling with covariates: Two improved three-step approaches. *Political Analysis, 18,* 450-469.

Vermunt, J. K., & Magidson, J. (2002). Latent class cluster analysis. In J. Hagenaars, & A. McCutcheon (Eds.), *Applied Latent Class Analysis* (pp. 89-106). Cambridge, UK: Cambridge University Press.

Viljaranta, J., Nurmi, J. E., Aunola, K., & Salmela-Aro, K. (2009). The role of task values in adolescents' educational tracks: A person-oriented approach. *Journal of Research on Adolescence*, *19*, 786-798.

Von Eye, G. & Bogat, A. (2006). Person-oriented and variable-oriented research: Concepts, results, and Development. *Merrill-Palmer Quarterly, 52,* 390-420.

Wang, C. P., Hendricks Brown, C., & Bandeen-Roche, K. (2005). Residual diagnostics for growth mixture models: Examining the impact of a preventive intervention on multiple trajectories of aggressive behavior. *Journal of the American Statistical Association*, *100*, 1054-1076.

Wang, M. & Degol, J. (2013). Motivational pathways to STEM career choices: Using expectancy value perspective to understand individual and gender differences in STEM fields. *Developmental Review, 33*, 304-340.

Watt, H. M., Eccles, J. S., & Durik, A. M. (2006). The leaky mathematics pipeline for girls: A motivational analysis of high school enrolments in Australia and the USA. *Equal Opportunities International*, *25*, 642-659.

Weiner, B. (1979). A theory of motivation for some classroom experiences. *Journal of Educational Psychology, 71,* 3-25.
Wigfield, A. (1994). Expectancy-value theory of achievement motivation: A developmental perspective. *Educational Psychology Review*, *6*, 49-78.
Wigfield, A., & Eccles, J. S. (2000). Expectancy–value theory of achievement motivation. *Contemporary Educational Psychology*, *25*, 68-81.
Wigfield, A., Tonks, S. & Eccles, J.S. (2004). Big theories revisited expectancy value theory in cross-cultural perspective. *Research on Sociocultural Influences on Motivation and Learning*. (pp. 165-198). Charlotte, NC: Information Age Publishing, Inc.
Wigfield, A., Tonks, S., & Klauda, S. L. (2009). Expectancy-value theory. In K. R. Wentzel & A. Wigfield (Eds.), *Handbook of Motivation at School* (pp. 55-76). New York, NY: Routledge.
Wilkins, N. J. & Kuperminc, G. (2009). Why try? Achievement motivation and perceived academic climate among Latino youth. *The Journal of Early Adolescence*, 30, 246-276. doi: 10.1177/0272431609333303
Wormington, S. V., Corpus, J. H., & Anderson, K. G. (2012). A person-centered investigation of academic motivation and school-related correlates in high school. *Learning and Individual Differences, 22,*427-438.
Zigler, E., & Kanzer, P. (1962). The effectiveness of two classes of verbal reinforcers on the performance of middle-and lower-class children. *Journal of Personality*, *30,* 157-163. doi: 10.1111/j.1467-6494.1962.tb01682.x
Zimmerman, B. J. (2000). Self-efficacy: An essential motive to learn. *Contemporary Educational Psychology*, *25*, 82-91. doi:10.1006/ceps.1999.1016