2017

The Impact Of Attitudes Toward Science And Core Self-Evaluation On Science Achievement And Career Outcomes: A Trajectory-Based Approach

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Abstract

A talented, innovative workforce in science, technology, engineering, and mathematics (STEM) is a critical component of sustained economic growth and global competitiveness. The development of this workforce is a primary concern among policymakers, industry leaders, and academics. Although many students express an interest in STEM in secondary school, many of them eventually choose not to pursue a degree or career in a STEM field. This trend has been linked to inadequate achievement, but also to lack of confidence, inconsistent interest, and shifting motivation. It is important that we understand the development of precollege socialcognitive factors affecting persistence to help identify whether some trajectories might have more desirable outcomes than others, and points at which intervention efforts might best be targeted. Growth mixture modeling was used in the current study to uncover unobserved developmental subgroups of students' attitudes toward science and positive core self-concept through their middle and high school years. Three distinct subgroups of change patterns were found for each of mastery motivation, attitudes toward science utility, and science self-concept. Science Self-Concept subgroups demonstrated significant and reasonably distinct associations with relevant science achievement, postsecondary, and career outcomes, where the results for Mastery Motivation and Science Utility subgroups were mixed. Science Utility and Science Self-Concept subgroups of developmental trajectories both exhibited plausible and appropriate associations with parent and demographic factors as well as initial student, parent, and teacher expectations about college and career.

Degree Type

Dissertation

Degree Name

Doctor of Philosophy (PhD)

Graduate Group

Education

First Advisor

Paul A. McDermott

Subject Categories

Educational Assessment, Evaluation, and Research | Educational Psychology

THE IMPACT OF ATTITUDES TOWARD SCIENCE AND CORE SELF-EVALUATION ON SCIENCE ACHIEVEMENT AND CAREER OUTCOMES: A TRAJECTORY-BASED APPROACH

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A DISSERTATION

in

Education

Presented to the Faculties of the University of Pennsylvania

in

Partial Fulfillment of the Requirements for the

Degree of Doctor of Philosophy

2017

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ACKNOWLEDGMENTS

To the many people who have offered guidance and support throughout my doctoral studies: I am profoundly grateful. To my committee especially I must express a sincere appreciation for your willingness to share your time, expertise, and wisdom. Dr. Paul McDermott, you have been unwavering in your encouragement, an unfailing source of constructive feedback and advice, and a terrific mentor, as evidenced by the invaluably many hours that we have spent discussing life and academics. Dr. Bob Boruch, thank you for your keen insights, and for pushing me to organize my thoughts around data quality. Dr. Michael Rovine, thank you so much for the incredible generosity and patience that enabled me to darken your doorstep so frequently with questions. And of course a heartfelt thanks to our program coordinator Christine Lee, and to all of the friends who readily lent me their ears.

A special thanks also to my family: Han-hsun & Joyce, Ariana & Michael, Brittany, and Elissa, and to Mary Talmadge-Grebenar and Ian Roy for being a constant and unconditional source of encouragement, support, and perspective.

ABSTRACT

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Paul A. McDermott

A talented, innovative workforce in science, technology, engineering, and mathematics (STEM) is a critical component of sustained economic growth and global competitiveness. The development of this workforce is a primary concern among policymakers, industry leaders, and academics. Although many students express an interest in STEM in secondary school, many of them eventually choose not to pursue a degree or career in a STEM field. This trend has been linked to inadequate achievement, but also to lack of confidence, inconsistent interest, and shifting motivation. It is important that we understand the development of precollege socialcognitive factors affecting persistence to help identify whether some trajectories might have more desirable outcomes than others, and points at which intervention efforts might best be targeted. Growth mixture modeling was used in the current study to uncover unobserved developmental subgroups of students' attitudes toward science and positive core self-concept through their middle and high school years. Three distinct subgroups of change patterns were found for each of mastery motivation, attitudes toward science utility, and science self-concept. Science Self-Concept subgroups demonstrated significant and reasonably distinct associations with relevant science achievement, postsecondary, and career outcomes, where the results for Mastery Motivation and Science Utility subgroups were mixed. Science Utility and Science Self-Concept subgroups of developmental trajectories both exhibited plausible and appropriate associations with parent and demographic factors as well as initial student, parent, and teacher expectations about college and career.

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Importance of Understanding the Structure and Development of the STEM Workforce

The state and shape of the U.S. workforce in the area of Science, Technology, Engineering, and Mathematics (STEM) has long been a prominent concern of policymakers, industry leaders, and academics. A talented, innovative workforce is a critical component of sustained economic growth and global competitiveness, and its development thus figures substantially in discussions as wide-ranging as education, health, environmental protection, national security, and immigration. Over the past decade, there has been an ongoing debate over the classification of STEM occupations, the directionality of the demand-supply gap of capable STEM workers, and the seemingly leaky pipeline between student-reported interest in STEM, completion of a post-secondary degree in STEM, and persistent employment in STEM (Landivar, 2013; Lowell & Salzman, 2007; National Science Board (NSB), 2015; Xue & Larson, 2015).

Definitions of STEM

Since there is a lack of consensus on the exact list of occupations that count as STEM, estimates on the number of people comprising that workforce ranged from 6 million to 21 million in 2013 (NSB, 2016), with 17% growth in the field expected from 2008 to 2018 (Langdon, McKittrick, Beede, Khan, & Doms, 2011). Technically, STEM is an acronym born of National Science Foundation (NSF) shorthand for those four domains in the 1990s, with many sources attributing the formal term (changed from "SMET") to Judith Ramaley in 2001, when she was assistant director of the education and human resources directorate at the NSF (Ostler, 2015). It is unclear whether the joining of those four disciplines under one umbrella term was meant merely to recognize their alliance in creating curricula, or if it was intended to signify a greater emphasis on integrating them. In education, current use of the term is widespread and mainly in reference to developing STEM education and promoting STEM literacy. Researchers and policymakers have identified scientific thinking as a critical competency for student success in the 21st century economy, even for those students who do not pursue STEM occupations. However, while this has implications for curriculum development and pedagogy, the broad economic and social benefits thought to be associated with both scientific thinking skills and specific STEM expertise in the workforce suggest that it is also the concern of other stakeholders, particularly those relevant to workforce development and equality.

The list of fields and occupations that comprise STEM varies widely among researchers, teachers, business leaders, and policymakers. The definitions differ depending on which agencies are doing the counting, and these different definitions yield different numbers. A Congressional Research Services report in 2012 attempted to summarize federal STEM investment inventory efforts over the seven years prior, reporting between 105 and 252 STEM programs engaged by 13 to 15 agencies, with annual federal appropriations of 2.8 to 3.4 billion, over half of which were intended for post-secondary needs (Gonzalez & Kuenzi, 2012). While most definitions agree on the inclusion of fields such as physics and computer science, some also include or exclude as diverse areas of study and occupations as health workers, social scientists, technicians, military media relations, agriculture, and management science. There are also different coding schemes, ranging from the NSF and National Center for Educational Statistics (NCES) Classification of Instructional Programs to the Census Standard Occupational Codes. Much of this variation in definition is likely attributable to differing purposes in collecting and analyzing the information: for instance, state of the workforce and rising industries from the perspective of the Departments of Labor and Commerce, education and grants from the Department of Education and NSF, immigration rules for the Department of Homeland Security Immigration Customs Enforcement. A study of faculty at an R1 institution in 2012 by Breiner, Harkness, Johnson and Koehler found that even academics conceptualized STEM differently depending on academic discipline and actual personal impact to them. An attempt at corralling the various coding schemes was made by a team at Ohio University in 2011 (Koonce, Zhou, Anderson, Hening, & Conley), but no standardization yet exists, making measurement of the components of the STEM workforce dependent on the context around data collection.

STEM Supply and Demand

With the question of definitions unresolved, then, it is not so surprising that there is also much debate about the directionality of the supply-demand gap of STEM workers. The answer as to whether there is a shortage or a surplus depends in large part on who is doing the asking, who is doing the answering, and their respective definitions of STEM. In 2007, a National Academies report highlighted low STEM retention rates and a lower percentage of STEM graduates in the U.S. than in other developed countries, recommending an increased emphasis on training science and mathematics educators for

K-12, further incentivizing higher education, and expanding funding for research and development (NAP). Equally as important is motivating students of all ages to pursue interests in STEM related classes. Meanwhile, a contemporary analysis of the STEM labor market found that only one of every two students graduating with a degree in STEM actually ended up employed in a STEM field (Lowell & Salzman, 2007). These individuals could be pursuing careers outside of STEM for a number of reasons including changing expectations, aspirations, or demographic factors. It could also suggest a surplus of STEM workers rather than a shortage, or be attributable to the myriad of definitions of STEM and the heterogeneity of the field and associated occupations (NSB, 2015; Xue & Larson, 2015). The latter adds another dimension to the supply-demand debate, acknowledging that entire STEM field does not move as one organism, containing as it does many disciplines, some of which are unrelated or require entirely different skill levels.

Although the conversation about STEM workers tends to revolve around those with Bachelor's and graduate degrees, there are many STEM occupations that do not require a four-year degree. As of 2011, half of all STEM jobs were middle-skill, requiring an associate's degree or occupational certification, and paid a wage 10% higher than other jobs with those educational requirements (Rothwell, 2013). The demand for middle-skill workers, combined with the fact that a majority of the two-thirds of STEM degree holders employed in non-STEM fields indicate that their jobs call upon skills from their STEM education (NSB, 2016), suggests that the pathway to STEM and its benefits are not always linear, nor necessarily dependent on higher education attainment.

Understanding the drivers and components of interest and persistence in STEM at different time points is crucial to informing our policies in developing the STEM workforce.

Persistence in STEM

There has been considerable research on STEM attrition, but much of it focuses on students who leave STEM fields in college (Bettinger, 2010; Chen, 2009; Chen & Soldner, 2014; Kokkelenberg and Sinha, 2010). A 2011 study from Georgetown University found that, ten years after receiving a STEM degree, 58% of STEM graduates were not actually employed in a STEM occupation. However, not all eventual STEM workers majored in a STEM field or even attended college, and many of the factors associated with attrition can be linked back to precollege considerations such as precollege academic preparation, high school science and math achievement, and STEM course-taking and performance (Chen & Soldner, 2014; Kokkelenberg and Sinha, 2010; Mendez, Buskirk, Lohr, & Haag, 2008; Ost, 2010; Rask, 2010; Shaw and Barbuti, 2010). Additionally, persistence has been associated with attitudinal factors such as motivation, confidence, and STEM self-efficacy, which are arguably more malleable than achievement and have also been considered possible factors in driving achievement (Aschbacher, Li, & Roth, 2010; Burtner, 2005; Huang, Taddese, and Walter, 2000). It is therefore important that we study precollege developmental trajectories to help identify points at which students drop into or out of that pipeline, whether some trajectories might have more desirable outcomes than others, and where intervention efforts might best be targeted.

There is a large body of literature dealing with possible strategies to affect student persistence in STEM. One strategy involves targeting high-achieving students, particularly those that have already demonstrated a talent in science or mathematics, with the expectation that those students are predisposed to better handle the rigorous coursework demands of STEM degrees. There is some evidence to support that high achieving students are more likely to complete STEM degrees and maintain STEM careers (Benbow, 2012; Crisp, Nora, & Taggart, 2009; Ma, 2011; Nicholls, Wolfe, Besterfield-Sacre, & Shuman, 2010; Rohr, 2012; Wang, 2013); however, that strategy alone would not necessarily fill the projected need, and is without regard for the diversity of the workforce or the multitude of STEM jobs that do not require college degrees. Another strategy pushes the focus away from achievement to social-cognitive factors such as attitudes, interests, and self-efficacy. This is built on the premise that developing positive attitudes toward science and mathematics might influence interest in STEM careers, and thereby motivation to achieve in those areas (Aschenbacher et al., 2010; Ing & Nylund-Gibson, 2013; Louis & Mistele, 2012; Osborne, Simon & Collins, 2003). This approach allows identification and cultivation of students with an interest in STEM without being dependent on demonstrated prior achievement, increasing the potential recruitment pool.

What Drives Interest and Achievement in STEM?

Most STEM majors choose science before they even enter college (Maltese & Tai, 2010, 2011). One-third of college freshmen indicate intent to major in a STEM field (Chen & Soldner, 2014), a decision that seems to be related to increasing interest in science and math rather than enrollment in particular courses or high prior achievement (Maltese & Tai, 2011). However, there is a preponderance of studies showing that many young people with an interest eventually choose not to pursue it, either at the high school or postsecondary level (Engberg & Wolniak, 2013; Hinojosa, Rapaport, Jaciw, LiCalsim & Zacamy, 2016; Miller & Kimmel, 2012; Riegle-Crumb & King, 2010; Wang, 2013). Research into how interests develop among adolescents is multi-faceted, with studies drawing connections to different motivational impetuses such as attitudes, achievement, personal strengths and self-concept, and family, peer, and environmental context (Aschbacher, et al., 2010; Denissen, Zarrett, & Eccles, 2007; Simpkins & Davis-Kean, 2005; Wigfield & Cambria, 2010).

Attitudes toward Science

Research in the area of identifying, measuring, and developing attitudes is motivated by a desire to increase student interest, performance, and retention. On the whole studies have mixed results, but tend to show that attitudes toward science do have some degree of association with persistence and performance. There has also been some investigation into influences on attitudes and predictors of attitudes, again with mixed results. As there are no standardized definitions or measurement instruments for attitude research, this lack of consensus or easy comparability across studies is not unexpected.

Definitions. The object of inquiries in this area can be divided into three main types: attitudes toward school science; attitudes toward real science, or toward science as a discipline more generally and in society; and scientific attitudes, or attitudes important for maintaining a scientific perspective and working in a scientific way (Gardner, 1975, 1996; Kind, Jones, & Barmby, 2007; Munby, 1997). The first is arguably most relevant to student interest and achievement, and will be the focus of this section. The definition of ‘attitudes’ itself embodies a variety of concepts, perhaps best described by Reid (2006) as falling into the three components of cognition, or knowledge about the object, affect, or feeling about the object, and behavior, or tendency toward action. Researchers studying attitudes toward science may conceptualize their object as only one of these, or all of them, or some interaction among them. Thus it is important when reviewing studies on attitudes to be clear on the definitions informing the research as well as the research hypotheses driving it.

Measurement of. Attitudes toward STEM subjects are generally evaluated by way of an assortment of constructs including perceived value of the subject, perceived utility of the subject to life or career goals, perceived academic efficacy in the subject, and reported interest in, enjoyment of, or anxiety toward the subject (Osborne et al, 2003). Most commonly they are measured using Thurstone-type or semantic differential scales, Likert scales, preference rankings, interest inventories, interviews, open-ended survey questions, and other self-report instruments (Gardner, 1975; Osborne et al, 2003). Occasionally an objective measure such as course enrollment might be included. Critiques of both the validity and psychometric properties of many of these instruments have been submitted by a myriad of researchers (Bennett, 2001; Francis & Greer, 1999; Gardner, 1996; Germann, 1988; Munby, 1983, 1997; Osborne et al, 2003, Reid, 2006; Schibeci, 1984). A comprehensive review of published psychometric evidence on science attitude instruments, encompassing the years 1935 to 2005, was conducted by Blalock et al. (2008) and found 66 instruments over 150 studies, few of which had enough reliability and validity evidence to recommended use. Kind et al (2007), recognizing need, attempted to develop psychometrically valid measures around science attitudes in context, including learning science in school, science outside of school, practical work in science, importance of science, self-concept in science, and future participation in science. They found that learning science in school, science outside of school, and future participation in science were able to load on one general attitude toward science factor.

Relationship with achievement and persistence. There are a number of studies devoted to understanding the interactions between these attitudes, their relationship with achievement and career outcomes, and potential influences on them. Student science achievement has been linked to positive attitudes in science (Martinez, 2002; Else-Quest, Mineo, & Higgins, 2013), and positive math and science attitudes linked to eventual employment in a STEM career (Ing & Nylund-Gibson, 2013), though there is some debate about the causal ordering of influence (Aschenbacher et al., 2010; Ma & Xu, 2004; Schibeci & Riley, 1986).

Although ‘attitudes’ and ‘interests’ are not interchangeable motivational concepts, they are strongly related. It is certainly logical that a positive interest in an object influences a positive attitude toward it. Conventional wisdom suggests that students are more likely to develop an interest in something that they expect to be useful either presently or in the future. Lacking actual subject area interest, they may also be more motivated to develop skills in areas that they nevertheless deem valuable to their life or career goals. This follows the expectancy-value theory (Wigfield & Eccles, 2000), which posits that individuals' expectations of their own competence and the degree to which they value an activity directly affect achievement, and also guide effort and persistence. Moreover, those expectations and values are influenced by social-cognitive variables such as individual goals, self-concept and ability beliefs. As these relate to future achievement motivation, Eccles et al. (1983) identified four different components of values: attainment value, or the importance of doing well; intrinsic value, or interest; utility value, or extrinsic, outcome expectant motivation; and cost, or the notion of ordering interests over limited time. Andersen and Chen (2016) applied this theory to investigate science-specific profiles of expectancy-value motivation in ninth-graders, using self-efficacy, attainment value of subject, utility value, and interest value. They found four distinct classes of student, with the 'low' group having low levels of all indicators, the 'typical' group have typical levels of all indicators, but the high self-efficacy group with lower levels of all other indicators, and the high utility group with low levels of self-efficacy. Notably, only 29% of the high ability students had a high expected value of science.

Growth in. Wilkins and Ma (2003) noted a decline in math attitudes and beliefs in math's social importance throughout secondary school; George (2000, 2003, 2006) found that the same was true for science attitudes, predicted by science self-concept, teacher and parent encouragement, and peer attitudes. He also found that there was positive growth in opinions about the utility of science over middle and high school, with predictors including science self-concept, teacher encouragement, achievement motivation, and engagement in science activities. Christidou (2011), somewhat conversely, observed that students rapidly lose interest in science in the transition to secondary school, while Barmby, Kind, and Jones (2008) found that attitudes toward learning science in schools declined but attitudes toward the importance of science and practical work remained constant. These findings suggest a possible attitudes effect in decisions about entry to and exit from the STEM pipeline.

Student Core Self-Evaluation

As related to interest, achievement, and persistence in STEM, research in the area of student self-concept and self-evaluation mainly focuses on the close link between self-efficacy, achievement, and declared interest—that is, the STEM field seems to draw high achievers, but also those who have high self-esteem and display higher self-efficacy rather than merely those declaring positive interests (McGeown et al., 2014; Potvin & Hasni, 2014). As well, self-efficacy and self-esteem are often studied in conjunction with academic motivation (Ommundsen, Haugen, & Lund, 2005; Ryan & Deci, 2006; Schunk, 1991). There have thus been forays into different motivational processes to aid in explaining differential performance and persistence, where intrinsic motivation is associated with engagement in an activity as its own reward and extrinsic motivation is driven by an outcome separable from the activity (Deci, Vallerand, Pelletier & Ryan, 1991; Eccles & Wifield, 2002; Taylor et al, 2014). Accordingly attributes related to self-confidence, self-worth, and self-determined motivational dynamics are included in consideration of success in STEM.

Definitions. When discussing student interests and achievement, the notion of self-concept tends to be limited to academic self-concept, specifically related to academic subject domains. However, there is a broader construct called *core self-evaluation (CSE)*, introduced by Judge, Locke, and Durham (1997), which integrates the concepts of self-esteem, generalized self-efficacy, locus of control, and emotional stability (low neuroticism) under one higher-order factor. Notably, many of these are also traits associated with adolescent resilience (Elliot, Kaliski, Burrus, Roberts, 2012). As self-esteem, self-efficacy, and general self-concept are empirically similar in regard to their correlations with other constructs and measurement methods, CSE can also be reduced to general self-concept and locus of control (Johnson, Rosen, Chang & Lin, 2016; Judge, Erez, Bono, & Thoresen, 2002; Wang & Su, 2013). General self-concept is based on an individual's self-assessment of their own competencies and capabilities, behavioral attributions, and assumptions and opinions about their environment (Debicki, Kellermanns, Barnett, Pearson, Pearson, 2016; Shavelson & Bolus, 1982). Locus of control is broadly defined as the extent to which an individual perceives that they can influence events and outcomes in their lives (Rotter, 1966). It is sometimes also referred to as sense of mastery (Erol & Orth, 2011; Falci, 2011). There is some question as to whether locus of control fits neatly into Judge et al.'s higher order core construct, or whether it is merely a related construct (Johnson et al., 2016). There is also some literature debating the strengths and limitations of considering CSEs as one aggregate construct rather than separate indicators, multidimensional scoring, and additional traits such as approach and avoidance motivation (Johnson, Rosen, & Levy, 2008).

Measurement of. CSEs as an aggregate or unidimensional construct have not been popularly studied in relation to academic achievement. Instead, researchers in education usually treat self-esteem and self-efficacy as separate but perhaps overlapping traits. Motivational attributes are usually scored separately and correlated or used as a predictor of other self-evaluations traits (Komarraju & Karau, 2005; Komarraju & Nadler, 2013; Zimmerman, 2000). Generally both CSEs and motivational constructs are measured using self-report scales, usually close-ended Likert or rating scales, and though there are more popular ones there is no one standardized measurement. For self-esteem, the Rosenberg Self Esteem Scale (1965) is generally the most widely used unidimensional measure. Self-efficacy scales are typically based around the recommendations of Bandura (1993; 2006) and tend to be constructed around a particular object area such as physical activity, mental health, or an academic discipline, as well as more generalized versions. The Mastery Scale (Pearlin & Schooler, 1978), comprised of seven Likert items, is a commonly used measure of locus of control. Aspects of the Big Five personality traits are often used as proxies or measures for self-evaluations where the constructs of concern relate to emotional stability (Costa & McCrae, 1992; Judge, Van Vianen, & DePater, 2004).

Relationship with achievement and persistence. CSEs have been linked to job satisfaction and job performance (Judge & Bono, 2001; Srivastava, Locke, Judge, & Adams, 2010), as well as motivation (Erez & Judge, 2001). Studies show that high ability students tend to demonstrate higher levels of self-esteem, self-efficacy, and locus of control (Bandura, 1997; Eccles, 2009; Eccles & Wigfield, 2002; Erol & Orth, 2011; Hildenbrand, 2009; Ma, 2002; Richardson, Abraham, & Bond, 2012; Wigfield, Eccles, Davis-Kean, Roeser, & Scheifele, 2006). These and related aspects of personality have also been associated with decisions to enroll in STEM majors (Chen & Simpson, 2015), and decisions at key points in the STEM pipeline (Jacobs, 2005; Simpkins & Davis-Kean, 2005). Researchers typically find that a high degree of intrinsic motivation is associated with academic success, though the results on extrinsic motivation are mixed (Lepper, Corpus, & Iyengar, 2005; Taylor et al, 2014; Vansteenkiste et al., 2004).

Growth in. Results of longitudinal analyses of self-evaluations factors have been inconsistent. Some investigators report gradual increases in self-esteem in Grades 7 through 12 (McCarthy and Hoge 1982, Nottelmann 1987), while others find that it declines during middle school (Rhodes, Roffman, Redd, & Frederiksen, 2004) or increases during adolescence and more slowly into adulthood (Erol & Orth, 2011; Pullmann, Allik, & Realo, 2009). There is some evidence that there is positive growth in both self-esteem and locus of control throughout high school (Falci, 2011), but also that locus of control becomes more internal each year between Grades 9 and 12 (Chubb, Fertman, & Ross, 1997) and that the transition to high school is accompanied by a decrease in self-efficacy (Bouffard, Boileau, & Vezeau, 2001). Studies of motivational change reveal a general decline as students progress through school, especially after a school transition (Eccles, Lord, Buchanan, 1996; Gottfried, Fleming, Gottfried, 2001; Otis, Grouzet, & Pelletier, 2005). However, a number of researchers have observed stability in self-concept and motivational measures over time (Chubb et al, 1997; Demo & Savin-Williams, 1992; Gottfried et al, 2001; Young & Mroczek, 2003).

Other Influences

Demographics. Gender and race have been shown to have or result in differential impacts on attitudes, self-concept, likelihood of employment in STEM careers, and achievement (Ing, 2014; Jacobs, 2005; Kimmel, Miller, Eccles, 2012; Riegle-Crumb et al, 2012; Sax & Harper, 2007; Wang & Degol, 2013). George (2000) found that attitudes toward science for boys followed a different trajectory in that they had higher initial status than girls and fell faster. Ing and Nylund-Gibson (2013) found that females and minorities were more likely to have positive attitudes toward STEM but were also less likely to be employed in a STEM career later. Erol and Orth (2013) observed that Hispanics demonstrated a lower initial self-esteem level than Whites, but that their trajectory increased strongly as they aged to young adulthood. Falci (2011) observed that females made steeper gains in self-esteem, and that students falling into higher socio-economic categorizations enjoyed a steeper rate of growth in both self-esteem and sense of mastery.

Expectations. Parent, student, and teacher expectations have been shown to have some effect on attitudes, self-concept, and achievement. Generally positive expectations and aspirations in regard to completing college and succeeding academically result in more positive attitudes, better self-esteem, and higher achievement, though there is some inconsistent evidence on both the effects and directionality of this (Aschbacher et al., 2010; George 2000, 2003; Grossman, Kuhn-McKearin, Strein, 2011; Hong, Yoo, You, Wu, 2010; Lakshmann, 2004; Ma, 2001; Sommerfeld, 2016).

Current Study

Purpose of the Current Study

The literature as summarized above paints an unclear picture with respect to the directionality and magnitude of temporal relationships related to attitudes toward science, student self-evaluations, persistence and achievement. Previous research suggests both that there are multiple dimensions of student attitudes toward science, such as opinions on utility of science and students' belief in their ability to succeed in science, and that there are variations over time in each of these dimensions (George, 2000, 2003, 2006). Prior studies also indicate that there are multiple dimensions of core self-evaluation, such as self-esteem and motivation, and that there are variations over time in each of these dimensions (Wang & Su, 2013). These dimensional variations, along with inconsistent findings related to growth and effects on achievement and persistence outcomes, support the likelihood that there might be multiple patterns of growth that correspond to unobserved subpopulations, which traditional growth models might mask with their single-population assumption.

The aim of this study is to investigate whether there are such subpopulations. By identifying unobserved subpopulations through growth mixture modeling, different classes of individuals are allowed to vary around different mean growth curves instead of individually varying around one mean growth curve as in latent growth curve analysis. This analysis will investigate the association between subgroups of changing attitudinal and core self-concept dimensions and later student outcomes.

Though there have been numerous studies focused on different aspects of positive self-concept and science attitudes as related to achievement, few of them have examined trajectories of those dimensions or groups of trajectories or related them to college and career outcomes. Examining groups of trajectories is an important contribution to the literature in that identifying such groups will enable better understanding of their development and potentially useful timing of interventions.

Also important in this exploratory investigation of latent longitudinal subgroups is characterizing these subgroups. Prior research suggests that possible risk factors related to the development of attitudinal and self-evaluation trajectories may include low parental education, low family income, and minority status. Additionally, the literature as previously reported points to possible effects of expectations on changing attitudes and self-evaluations. Initially high (grade 7) student, parent, and teacher expectations concerning college attendance, achievement in science, and careers in STEM may increase likelihood of membership in more desirable subgroups.

Research Questions

Based on a review of the current literature, this study was designed to explore the following research questions (RQs):

(1) Are there latent and longitudinal subgroups (developmental trajectories) of student positive self-concept as they progress through middle and high school?

(2) Are there latent and longitudinal subgroups (developmental trajectories) of student attitudes toward science as they progress through middle and high school?

(3) Do these (A) self-concept and (B) attitudinal subgroups signal student science achievement at the end of high school?

(4) Do these (A) self-concept and (B) attitudinal subgroups signal student college and career outcomes?

(5) To what extent are initial parent and demographic factors associated with memberships in these (A) self-concept and (B) attitudinal subgroups?

(6) To what extent are initial student, parent, and teacher expectations associated with memberships in these (A) self-concept and (B) attitudinal subgroups?

CHAPTER 2: METHODS

Data

Sample

Data are drawn from the Longitudinal Study of American Youth (LSAY), a project funded by the National Science Foundation in 1985-1994 and 2007-2011 to investigate the development of student attitudes toward math and science, achievement in math and science, and student interest in pursuing a career in science, technology, math, or engineering. There were two cohorts: Cohort One (N = 2,829), followed from 10th grade to four years post-high school; and Cohort Two (N = 3,116), followed from 7th grade to one year post-high school. The sampling frame was public high schools throughout the United States, with participants in Cohort Two drawn from public middle schools that served as feeder schools to the high schools which the older cohort was drawn from. The sample design was a two-stage stratified probability sample, with public schools serving grades 10-12 selected from 12 strata identified by geographic region (Northeast, Midwest, South, West) and level of urban development (urban, suburban, rural) and random selection of 60 students from each selected school. For Cohort Two, the high school officials provided information on whether their school included the middle school grades, whether there was one feeder school, or whether there were multiple feeder schools. In the latter case the proportion of students enrolled in the high school from each feeder school was calculated and then one was randomly selected, where the probability of selection corresponded to that proportion. The total number of high school and feeder school pairs included in the study was 51, with 18% Northeast, 31% North Central, 33% South, 18% West and 24% Urban, 43% Suburban, 33% Rural.

An extensive array of information was collected from students, parents, teachers, and principals from 1987-1994, including annual standardized achievement tests, parent interviews, school-level context information, and questionnaires on attitudes, experiences, course enrollment and performance, and classroom practice. A follow-up study on educational and occupational outcomes was proposed and funded in 2006, tracking both the original LSAY participants and a new sample of approximately 5,000 students. Researchers were able to locate approximately 95% of the original combined cohort. The follow-up included a series of five surveys conducted from 2007 to 2011, with varying response rates.

This study focuses on data from Cohort Two, as that sample covered more years relevant to the planned analysis. Student and parent instrument response rates for Cohort Two (1987-1994) ranged from .99 (Science Test, Fall 1987) to .47 (Mathematics Test, Fall 1992), with an average of .76. As the data collection structure for LSAY as a whole was complex and involved multiple informants, types of instruments, and forms across a number of years, the decision was made to draw variables constructed from the student questionnaires exclusively to investigate the proposed research questions. Although some sampling weights were provided in the analysis file, these lacked context for the current study and so were not used. Selected demographic characteristics of the sample are provided in Table 1.

Table 1. *Sample Demographic and Parent Characteristics*

Descriptive Statistics	*n*	Percent
Student sex		
Male	1626	52.2
Female	1490	47.8
Student race[a]		
Hispanic	284	9.6
Black	349	11.8
Other	2324	78.6
Parent highest education[b]		
High school or less	1666	54.5
Some college	433	14.2
BA or higher	957	31.3
Parent employed in STEM[c]		
No	2421	81.1
Technical	409	13.7
Professional	157	5.3
Region		
Northeast	618	19.8
Northcentral	951	30.5
South	1019	32.7
West	528	16.9
Community		
Urban	797	25.6
Suburban	1367	43.9
Rural	952	30.6

[a]Missing data for 159 students.
[b]Missing data for 60 students.
[c] Missing data for 129 students.

Measures

Attitudes toward science measures. A set of ten questions related to enjoyment of science, anxiety about science, and perceived usefulness of science was included in every fall student questionnaire. The questions are set on a five-point Likert scale from "Strongly Agree" to "Strongly Disagree". Previous literature utilizing this measure seems to simply select items based on face validity to the attitudinal aspect that the researcher is attempting to examine (ie. George, 2000, 2003, 2006; Ing & Nylund, 2013; Ma & Cartwright, 2003; Ma & Xu, 2004), and if reliability is reported it is for a specific subset of questions and population. Thus there seems to be little information on psychometric properties available, and an examination of dimensionality was required as a preliminary step in investigating the research questions.

Self-Evaluation measures. A set of seventeen questions related to self-esteem, approach motivation, and locus of control was included in every fall student questionnaire. The questions are set on a five-point Likert scale from "Strongly Agree" to "Strongly Disagree", and begin with the stem "How do you feel about each of the following?". The questions appear to be a mix of items that are also used in NCES surveys (the locus of control items), six of the ten items from the Rosenberg self-esteem scale (1965), and some other items that have no clear origin. Note that the original Rosenberg self-esteem scale was set on a four-point Likert scale, with scores calculated by summing over all items. Although the validity and reliability of this scale has been well studied, in this case there is a different number of items, a different number of response choices, and the items are mixed with those reflecting slightly different constructs. Other studies using the LSAY to investigate these measures rely on face validity to select representative items; thus an examination of dimensionality was required for the current study.

Distal outcome measures. Several items included in the student questionnaires were used to investigate outcomes. One outcome, student achievement, is more proximal, and was drawn from the Grade 12 questionnaires. Student college and career outcomes were drawn from the 2007-2011 questionnaires. As an update on education and occupation is given in every subsequent questionnaire and the follow-up of the original cohort took place over years, summary measures were used or constructed where possible.

Student achievement outcomes. Student achievement was measured using advanced science coursework (highest science course taken and number of courses above biology), science course grades, and science standardized tests. The latter were given every fall and developed from NAEP item pools. Scores were calibrated using multiple group IRT scoring, and then converted to a scale with mean of 50 and standard deviation of 10. Missing scores were imputed unless the student dropped out of school or was missing four or more scores. There is an aggregate test and three subscales for biological science, physical science, and environmental science—this analysis uses the aggregate. As there is no indication that a proficiency benchmark was set for this norm-referenced test, this research followed the example of the related constructed variables in the dataset and categorized scores into quintiles.

Student college and career outcomes. Student college and career outcomes include whether the student obtained a BA/BS, a BA/BS in STEM, started with a major in STEM, was employed in a STEM career (professional or support occupation), and whether the student completed graduate work in STEM.

Longitudinal Missing Data

In a multi-year, multi-site study, it is not unusual for data to be incomplete, as many participants relocate or are otherwise not available for evaluation at all timepoints. Additionally, participants may choose to skip questions they do not want to answer or to complete only some parts of the questionnaire, especially in what might be considered a low-stakes environment. Thus this study presents a rather complicated missing data problem. As in many longitudinal studies, there are clear signs of attrition, where the number of students in the dataset decreased from 3,116 in timepoint 1 (Grade 7) to 2,397 in timepoint 6 (Grade 12). For the purposes of this study, further examination of missing data patterns was restricted to the variables comprising the two sets of items that represent the constructs at the focal point of the research (Student Self-Evaluation and Attitudes toward Science).

Case Level Missingness

Patterns of missing data were examined for each item set separately. They were first evaluated at case level by timepoint, where a case was considered missing in a timepoint if no items were completed in the set and nonmissing if at least one item was completed.

For Student Self-Evaluation, there were 48 patterns of missingness by timepoint, of which five were patterns of monotonically missing (1,239 cases, or about 63.3% of total missing) and the rest intermittent. There were 1,158 cases with at least one completed item in every timepoint, 4 cases missing all timepoints, and 15% missing data for more than three timepoints. Examination of the Attitudes toward Science items revealed 50 patterns of missingness by timepoint, of which five were patterns of monotonically missing (1,236 cases, or about 60.9% of total missing) and the rest intermittent. There were 1,086 cases with at least one completed item in every timepoint, 6 cases missing all timepoints, and 15% missing data for more than three timepoints. Tables 2 and 3 respectively enumerate the nonmissing and complete cases for each item set by timepoint. Although the portion of nonmissing cases decreased appreciably over time, the percentages of nonmissing cases with complete data remained fairly high, with the lowest at 79.9% and an average of 89.3%.

Table 2. *Nonmissing Cases by Timepoint and Item Set*

Timepoint	Item Set	*n*	Percent[a]
Grade 7	Student self-concept	3078	99.0
	Attitudes toward science	3062	98.0
Grade 8	Student self-concept	2703	87.0
	Attitudes toward science	2667	86.0
Grade 9	Student self-concept	2376	76.0
	Attitudes toward science	2339	75.0
Grade 10	Student self-concept	2268	73.0
	Attitudes toward science	2258	72.0
Grade 11	Student self-concept	2008	64.0
	Attitudes toward science	1976	63.0
Grade 12	Student self-concept	1581	51.0
	Attitudes toward science	1544	50.0

[a]Out of N = 3116

Item Level Missingness

Inasmuch as the portion of nonmissing cases with incomplete data at a given timepoint ranged between 4% and 20%, item-level missingness was also assessed for each set of items. Analysis revealed both monotone and intermittent patterns. Of nonmissing incomplete cases over timepoints, most were missing less than two items, ranging from 87.2% (timepoint 1) to 93.8% (timepoint 4) for Student Self-Evaluation items and from 90.7% (timepoint 1) to 96.5% (timepoint 4) for Attitudes toward Science items, with an average of 92.4% overall. A small percentage of nonmissing incomplete cases was missing more than half of the items at a given timepoint, ranging between 1.0% (timepoint 5) and 4.0% (timepoint 1) for Student Self-Evaluation items and 1.9% (timepoint 2) and 6.6% (timepoint 6) for Attitudes toward Science items.

Table 3. *Complete Data by Timepoint and Item Set*

Timepoint	Item Set	*n*	Percent[a]	Percent of Nonmissing[b]
Grade 7	Student self-concept	2452	79.0	79.9
	Attitudes toward science	2708	87.0	88.4
Grade 8	Student self-concept	2203	71.0	81.5
	Attitudes toward science	2453	79.0	92.0
Grade 9	Student self-concept	2063	66.0	86.8
	Attitudes toward science	2167	70.0	92.6
Grade 10	Student self-concept	1960	63.0	86.4
	Attitudes toward science	2116	68.0	93.7
Grade 11	Student self-concept	1804	58.0	89.8
	Attitudes toward science	1870	60.0	94.6
Grade 12	Student self-concept	1419	46.0	89.8

Attitudes toward science	1483	48.0	96.0

[a]Out of N = 3116
[b]Denominators from Table 1

Imputation

As listwise deletion is strongly recommended against in almost all cases (Allison, 2002), and would result in a drastically reduced dataset of 577 for Student Self-Evaluation items and 761 for Attitudes toward Science items, an imputation strategy was necessary. Formulation of this strategy involved consideration of missing data at both case level and at item level, with both monotone and nonmonotone patterns. Since the ultimate purpose of this study is to examine trajectories, the decision was made to preserve the case level missingness (both intermittent and due to attrition) during this item-level imputation. In order to avoid bias associated with possible autocorrelation of items across time, account for monotone missing data patterns within each item set, and avoid imputing for individuals not in particular timepoints, each timepoint was imputed separately.

Missing values were considered to be arbitrarily missing at random within timepoints, and imputed using a Markov Chain Monte Carlo (MCMC) multiple imputation (MI) method as recommended by D. B. Rubin (1987) and Schafer (1997). Although the normal based approach to MI assumes a multivariate normal continuous distribution that is not generally appropriate for categorical data, Schafer noted that the MIC approach is impractical for most real world problems with larger numbers of variables (1997). Lee and Carlin (2010) also observed that in general fully conditional specification methods and multivariate normal imputation produce similar results even in the presence of ordinal variables. There has been much debate in the literature over whether using the normal based approach and naively rounding noninteger values for categorical and ordinal variables introduces unacceptable error into parameter estimates or not (eg. Allison, 2005; Finch, 2010; Lee et al, 2012; Leite & Beretvas, 2010; Rhemtulla, Brousseau-Liard, & Savalei, 2012) with the general consensus that the relevance of this depends on the purpose of imputation, number of categories, sample size, and symmetry of variable distribution. There is some evidence that imputing data with five or more ordered categories using MI yields acceptable correlation estimation results with about 10% of missing data, and up to about 30% (Leite & Beretvas, 2010). Additionally, studies have found that multinomial logistic regression and proportional odds methods specifically designed for polytomous data perform more poorly in many situations than the normal model with naïve rounding (Finch, 2010; Wu, Jia, & Enders, 2015). MI without rounding has been recommended as an appropriate approach (Allison, 2005; Wu, Jia & Enders, 2015), but this is not suitable for an analysis that requires ordinal variables at item level for analysis. Other rounding strategies (e.g. adaptive, two-stage calibration) are cumbersome to implement and not better (Lee et al, 2012).

Fifty imputations of each dataset were performed (Bodner, 2008; Graham, Olchowski, & Gilreath, 2007). Since the dimensional analysis requires one integer value for each item, these imputations were then averaged into a single point estimate for each variable for each timepoint. Although literature proposes performing a dimensional analysis on all imputed datasets and comparing effects across them, many different decisions to make in regard to rotation, this would be impractical to implement. Effects on the correlation matrix were analyzed and found acceptable, with efficiency greater than .99

Dimensionality

Dimensional analysis for both sets of items was performed in R Version 3.3.2 (R Core Team, 2016) using the packages psych (Revelle, 2016) and lavaan (Yves Rosseel, 2012).

Exploratory analysis. Exploratory factor analysis (EFA) was conducted for both sets of items. To ensure equal coverage of all six timepoints, a two-stage sampling process was used. First, one timepoint was randomly selected for each individual so that each individual was represented only once. Then a group of 140 individuals was randomly selected for each timepoint, for a mutually exclusive total sample of 840.

The sample was randomly split into exploratory and confirmatory subsamples. Minimum average partialling (MAP; Velicer, 1976) was employed to suggest a preliminary estimate of retained number of factors. Iterated common-factor models were rotated toward simple structure using varimax, equamax, and promax rotations. The preferred solution for each respective dimension (dependent variable) was based on (a) item coverage and simple structure with maximized hyperplane count (Yates, 1987); (b) at least three salient items (loadings $\geq .35$); (c) sufficient reliability (i.e., $\alpha \geq .70$); and (d) parsimonious coverage of content and compatibility with leading research and theory (Fabrigar, Wegener, MacCallum, & Strahan, 1999).

Confirmatory analysis. The factor structures obtained from EFA for each dependent variable were submitted to CFA with the confirmatory subsample using weighted least squares means and variance adjusted (WLSMV) estimation. WLSMV is a robust diagonally weighted least squares approach specifically designed for ordinal data that makes no distributional assumptions (Brown, 2006). Acceptable fit criteria corresponded to a Root Mean Squared Error of Approximation (RMSEA) ≤ .08 and a Comparative Fit Index (CFI) ≥ .90 (Marsh, Liem, Martin, Morin, & Nagengast, 2011).

Longitudinal Measurement Invariance

As this analysis involves tracing growth in constructs, it is necessary to ensure measurement of the same construct over time. Measurement invariance within an SEM framework is usually assessed using a series of nested models, adding restrictions to each subsequent model and testing for change in fit compared to the less constrained model. For the purposes of this research, four models were tested for each set of items: configural invariance, to determine equivalent factor structure across time; metric invariance, constraining factor loadings over time; scalar or strong invariance, constraining intercepts; and strict invariance, with equal residuals across occasions.

Robust maximum likelihood was used to estimate models as Browne (1984) and Rhemtulla, Brosseau-Liard and Savalei (2012) suggest is acceptable for ordered categorical likert scale items with five categories. Scaled chi-square difference tests (Satorra & Bentler, 2001) were conducted to examine measurement invariance as recommended for nested models. However, as these suffer from a dependence on sample size, model fit was also evaluated using CFI and RMSEA (Cheung & Rensvold, 2002).

Criteria used to indicate an unacceptable decrement in fit included a decrease in CFI ≥ 0.01 and an increase in RMSEA ≥ 0.015 as proposed by Chen (2007). Generally, a demonstration of at least partial strong invariance is recommended for comparing latent means across time. While the planned analysis in this research is to use IRT scaling methods, establishing at least configural invariance for each set of items is necessary in order to ensure that each scale contains the same items across occasions.

Scaling

Salient items on each respective factorial dimension were scaled through IRT using flexmirt (Cai, 2013), with application of generalized partial credit logistic and graded response models to polytomous items. Models were selected that maximize slopes and reliability of information. Akaike's information criterion (AIC; Akaike, 1987) and Schwarz's Bayesian information criterion (BIC; Schwarz, 1978) were used to assess models (Kang, Cohen, & Sung, 2009), with minimal values preferable. Scores were computed via the Bayesian Expected a Posteriori (EAP) method and centered at $M = 50$ and $SD = 10$ for easier interpretation. Factor reliability was assessed using Cronbach's α and McDonald's omega. As the small number of items per dimension made any vertical equating procedure unfeasible, the models were based on the first measurement (Grade 7), with the resultant parameters then being applied to the other five timepoints.

Latent Growth Mixture Models

Latent growth mixture modeling (Duncan, Duncan, & Strycker, 2006; Ram & Grimm, 2009) was used to identify unobserved subgroups of longitudinal change in each self-evaluation and attitudinal dimension. Models for each dimension were estimated separately applying both fixed (linear and polynomial) and latent basis approaches across the six timepoints (see Figure 1).

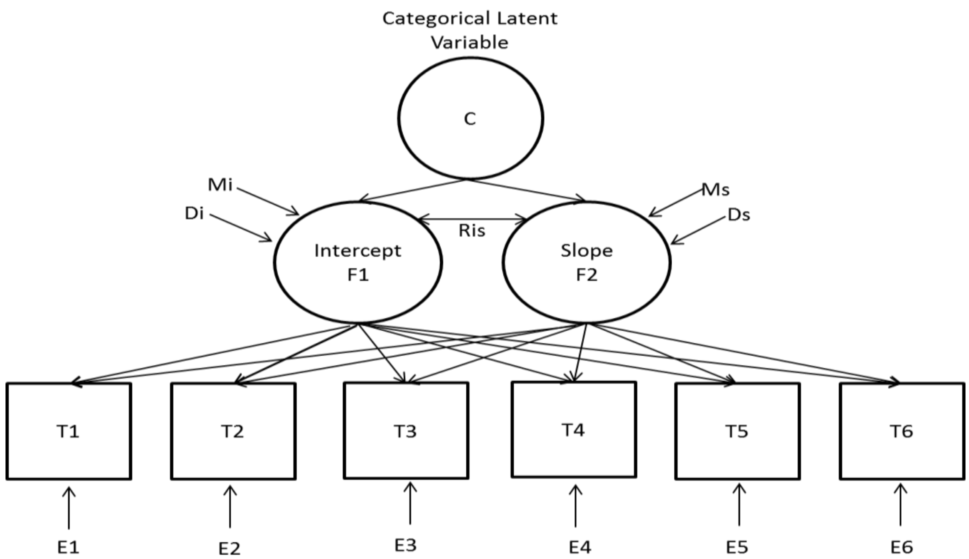

Figure 1. Representation of the latent variable growth mixture model.

A single latent growth curve model was fitted for each dimension in order to determine whether the residual variances should be allowed to vary across occasions. In cases with differing amounts of available data over time, free estimation of the residuals often tends to provide better fit. Model criteria include (a) lower values for Akaike's Information Criterion (AIC), Scharwz's Bayesian Information Criterion (BIC), and Adjusted BIC (ABIC) than found in simpler models (Nylund, Asparouhov, & Muthen, 2007), (b) minimal values for the Integrated Classification Likelihood with Bayesian-type Approximation (ICL-BIC; McLachlan & Peel, 2000), (c) maximal values for entropy and average posterior classification accuracy (Greenbaum, Del Boca, Darkes, Wang, & Goldman, 2005; Nagin, 1999), (d) statistically significant contrast with the model comprised of one less latent class as per the Vuong-Lo-Mendell-Rubin, Lo-Mendell-Rubin, and parametric bootstrap (with 100 draws) likelihood ratio tests (Nylund et al., 2007), (e) results supported by theory (Ram & Grimm, 2009).

Mplus version 7.4 (Muthen & Muthen, 2015) was used for all analyses, with missing scores on cases for each dimension forced into monotone missingness so that all timepoints after the first missing timepoint were also missing. This was intended to smooth the dropout into a normal attrition pattern so that trajectories could be better estimated (Glynn, Laird, & Rubin, 1986; Marini, Olsen, & Rubin, 1980; Newsom, 2015). Imputation of missing data for this analysis was performed under full-information maximum-likelihood (FIML) estimation.

Distal Outcomes Models

Given the selected growth models for attitudinal and self-concept dimensions, binary distal student outcomes were produced and regressed on the resultant latent subgroups (classes) (see Figure 2). Binary outcomes were applied to determine the relative probabilities of desirable compared to undesirable outcomes (in 12th grade for science achievement, and in 2007-2011 for college and career outcomes), as a function of latent growth class membership. Binary variables were generated for each outcome if not already binary, with the category or quintile of interest coded as 1 and the remaining categories coded as 0. Probabilities of better versus poorer outcomes associated with each latent growth class were obtained using the M*plus* DCAT function.

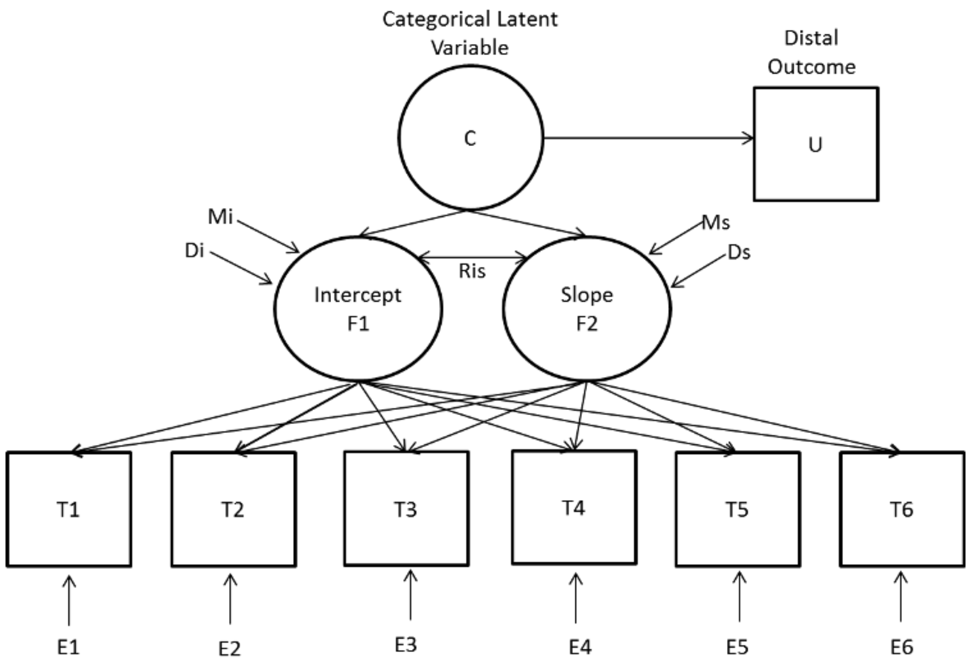

Figure 2. Representation of the latent variable growth mixture model, with latent subpopulations predicting a distal outcome.

Advanced science coursework. Binary outcomes related to advanced science coursework included highest science course through Grade 12 and number of science courses above biology. As the intent behind these variables was to establish coursework above and beyond the typical, the category ‘physics/advanced’ was coded 1 for highest science course and the count of 4 or more for number of science courses (1 or more standard deviations above the population mean).

Achievement. Variables were constructed for both the highest and lowest quintile of the science standardized achievement test administered in Grade 12. A set of four dichotomous outcome variables were formed for grades in science coursework, where 1 represented either As/Bs or below Cs depending on the variable, one each for science grades in Grade 12 and science grades on average.

College and Career. Variables on college and career were already binary, and the public use dataset provided summary variables that aggregated responses across years of the follow-up study. One variable was constructed for the purpose of this research to identify whether a student had ever reported being employed in either a STEM career or a STEM support career.

Risk Factors Models

The 3-step method (Asparouhov & Muthen, 2014) was applied in the regression of latent change classes on explanatory covariates representing parent and demographic characteristics, while accounting for measurement error in posterior classifications (See Figure 3). The first set of models include the parental and demographic variables as simultaneous binary applied explanatory variables (minority status vs. not, female vs. not, parent with BA vs. not, parent employed in STEM field vs. not) in a multinomial logistic regression model applying the general logit link function. The goal was to investigate the relative risk reduction or risk increment (estimated through the odds ratio) associated with demographic and parent characteristic variable. The second set of models include the expectations variables as simultaneous binary applied explanatory variables (teacher expects college vs. not, teacher encourages career in science vs. not, parent expects do well in science vs. not, parents expect college vs. not, parents would like student STEM career vs. not, student expects 4-year college vs. not, student expects 2-year college vs. not, student expects STEM vs. not) in a multinomial logistic regression model applying the general logit link function. The goal was to investigate the relative risk reduction or risk increment (estimated through the odds ratio) associated with expectations variable.

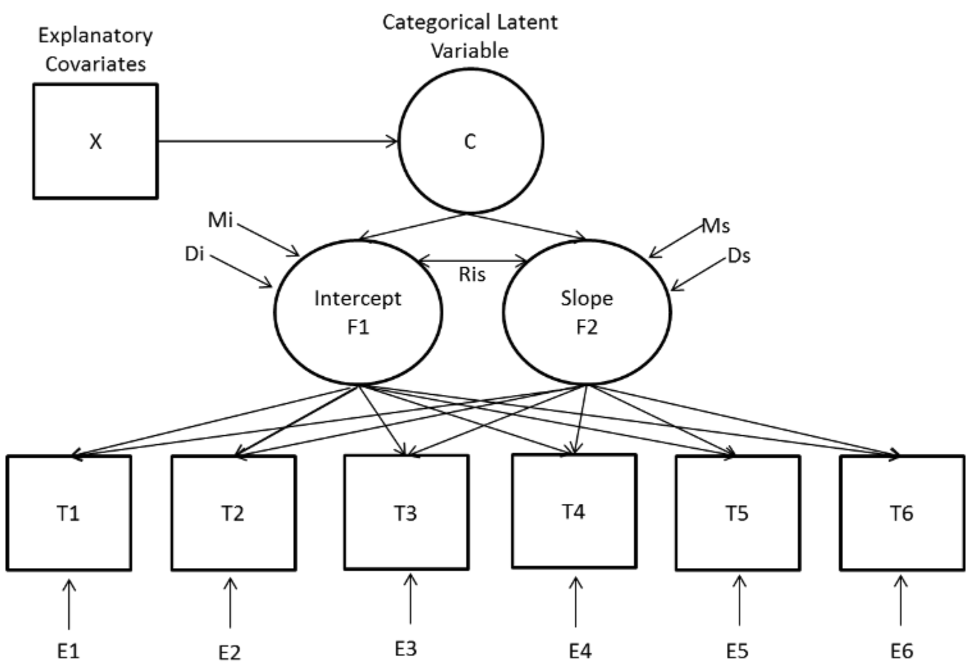

Figure 3. Representation of the latent variable growth mixture model, with explanatory covariates predicting latent subpopulations.

CHAPTER 3: RESULTS

Student Self-Evaluations

As a preliminary to the main analysis, means, correlations, and distribution statistics were calculated for all self-evaluations items to ensure that skewness and kurtosis were within acceptable ranges for relatively normal distributions and correlations were in the expected directions. All values for skewness and kurtosis were between -1 and 1, indicating an acceptable approximation of normality.

Dimensionality

MAP for the17 items related to student self-concept suggested that a minimum of 3 factors might be extracted from the smoothed polychoric correlation matrix. Models containing 1, 2, 3, and 4 factors were assessed against the stated criteria. The 1- and 2-factor models were found to compress items into less meaningful composites and the 4-factor model produced uninterpretable and unreliable scales. The 3-factor model was determined as the optimal solution to meet all criteria. Five nonsalient items were removed before subsequent analyses.

Table 4 displays rotated pattern loadings, final communalities, product-moment item-scale correlations, and coefficients α (as a lower bound) and ω_t (as a higher bound) for each scale. Based on patterns of descending loadings and item content, the scales were named Self-Esteem (4 items), Locus of Control (5 items), and Mastery Motivation (3 items).

Table 4. *Dimensional Structure and Properties of the Core Self-Evaluation Measure*

	Scale pattern loadings[b]				
Item description[a]	I	II	III	Commu-nality	Item/ scale r^{c}
	Self-Esteem (coefficient α = .79[e], ω_t = .83)				
I am a person of worth	*.79*	-.11	-.13	.62	.72
Positive attitude toward self	*.74*	-.06	.05	.62	.72
Able to do things as well as others	*.69*	-.15	-.03	.57	.65
Generally satisfied w/ self	*.68*	-.08	.01	.51	.63
	Locus of Control (coefficient α = .70[e], ω_t = .75)				
Plans hardly ever work out	.00	*.66*	-.03	.43	.59
Feel I am a failure	-.29	*.65*	.08	.62	.68
Try get ahead, thwarted	-.03	*.63*	.00	.41	.57
Wish I respected myself more	-.16	*.52*	.03	.35	.53
Good luck more important than work	.08	*.47*	.03	.20	.39
	Mastery Motivation (coefficient α = .69[e], ω_t = .74)				
Like working on tough problems	-.08	.01	*.84*	.66	.69
Like to keep struggling w/ problems	-.03	.04	*.74*	.52	.65

Table 4 (continued)

Like to figure things out for myself	.03	.12	*.56*	.33	.50

[a]Item descriptions are abbreviated for convenient presentation.
[b]Values are promaxian pattern loadings. Salient pattern loadings (≥ .40) are italicized.
[c]Each correlation reflects the relationship between an item and the sum of the other items comprising a scale, where distributions were standardized to unit-normal form.
[e]Reliability is based on the sample *N* = 420.

The four items on the Self-Esteem scale were the four positive items from the Rosenberg (1965) self-esteem scale that had been included on the questionnaire, relating to attitude toward self and self-competencies. The two negative items from the Rosenberg scale clustered with the NCES Locus of Control items, where the scale represents sense of control over the outcomes in one's life and is often associated with attribution of success to fate. Mastery Motivation is a dimension of intrinsic motivation further elucidated by Harter (1975), defined as the desire to solve problems independently for the sake of finding the solution. Interfactor correlations were as follows: -.37 for Self-Esteem and Locus of Control, .43 for Self-Esteem and Mastery Motivation, and -.12 for Locus of Control and Mastery Motivation.

The three-dimensional structure was validated with the confirmatory subsample. Model fit was good with $\chi 2$ (51) = 85.142, CFI = .956, and RMSEA = .04 (90% CI = .024-.055).

Longitudinal Measurement Invariance

Although all scaled chi-square tests were significant, this is not uncommon for a test statistic dependent on sample size, with research indicating it will likely be significant for large sample sizes (Gerbing & Anderson, 1985). Literature further suggests that the focus of measurement invariance testing for large samples should therefore be absolute and relative fit profiles (Cheung, 2002). The configural model demonstrated adequate fit at CFI $\geq$ .90 and RMSEA $\leq$ .08, and subsequent further restricted models for metric and scalar invariance did not contribute to an unacceptable loss of fit. Model fit statistics and associated decrements are displayed in Table 5.

Table 5. *Measurement Invariance for Student Self-Evaluation*

Model	CFI	ΔCFI	RMSEA	ΔRMSEA
Configural	.944	---	.024	---
Metric	.943	.001	.024	.000
Scalar	.936	.007	.025	.001
Equal residuals	.906	.030	.030	.005

Scaling

AIC and BIC values for each of the three dimensions suggested that the graded response model was a better fit to the data than the generalized partial credit model. The graded response threshold parameters for Self-Esteem ranged -1.03-3.28 (*M* = 1.30, *SD* = 1.48) and slopes 1.59-1.76 (*M* = 1.68, *SD* =0.06); the response threshold parameters for Locus of Control ranged -2.57-2.67 (*M* = -0.41, *SD* = 1.58) and slopes 1.00-1.55 (*M* = 1.28, *SD* =0.21); the response threshold parameters for Mastery Motivation ranged -1.90-3.33 (*M* = 0.78, *SD* = 1.53) and slopes 1.01-2.76 (*M* = 1.68, *SD* =0.77). EAP (Thissen, Pommerich, Billeaud, & Williams, 1995) scaled scores (*SS*s) for each dimension were produced, centered at *M* = 50 and *SD* = 10, with higher scores indicating greater levels of positive self-evaluations for Self-Esteem and Mastery Motivation and negative self-evaluations for Locus of Control. The scales were internally consistent with Self-Esteem yielding an α coefficient of .79, Locus of Control an α coefficient of .70, and an α coefficient of .69 for Mastery Motivation. Though the Mastery Motivation dimension fell below the recommended acceptable α criterion of .70, the dimension was retained as it performed well in the confirmatory analysis, and generated an ω_t above .70. Marginal reliability for response pattern scores was .73, .70, and .72 for Self-Esteem, Locus of

Control, and Mastery Motivation, respectively. See Figures 4, 5, and 6 for overlay plots of test information functions and standard error curves.

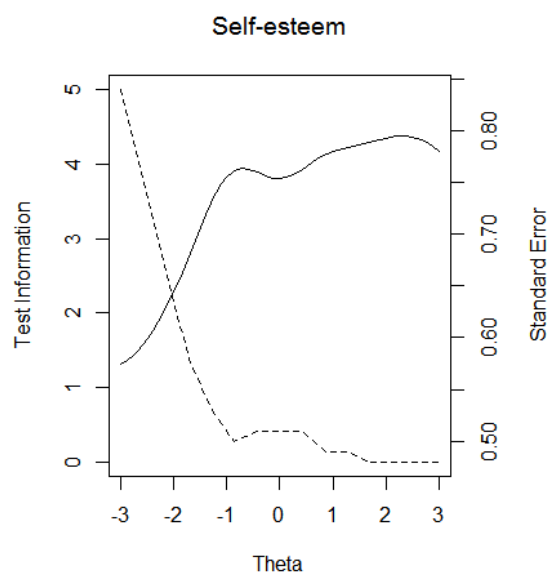

Figure 4. Distributions of estimated information functions and standard errors for Self-Esteem scale

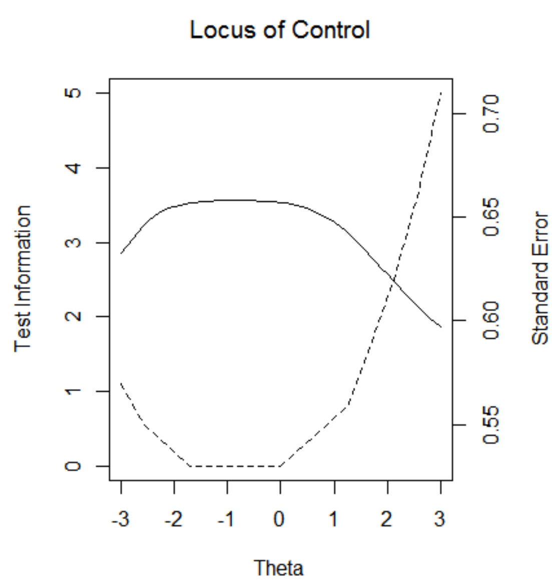

Figure 5. Distributions of estimated information functions and standard errors for Locus of Control scale

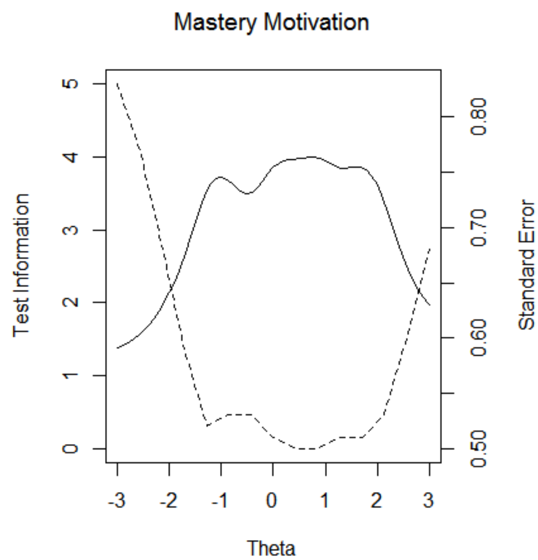

Figure 6. Distributions of estimated information functions and standard errors for Mastery Motivation scale

Latent Growth Mixture Models

Models as derived from polynomial growth estimates consistently demonstrated better fit than those estimated using latent basis estimation. Results of models are reported below by core self-evaluation dimension.

Self-Esteem. The models for Self-Esteem were found to fit best while estimating quadratic growth. Properties, fit statistics, and parameter estimates for these models are reported in Table 6. No model was deemed acceptable. The 2-class model exhibited minimal ICL-BIC, maximal entropy, and maximal classification accuracy, but failed to provide a second class with sufficient membership where sufficient was set at approximately 100 individuals. Although the literature commonly advises 1% of sample as the minimum for class membership (Jung & Wickrama, 2008), and 5% is generally the benchmark for practical use, this research considered 1% inadequate for powering further planned analyses where 3% (or about 100 individuals) would be acceptable. The 3-class model resulted in unacceptably low entropy. The 4-class model, while demonstrating minimal AIC, BIC, and ABIC, acceptable entropy and classification accuracy and passing the likelihood ratio tests (LRTs) for significant improvement over the 3-class model, generated a class with insufficient membership. The 5-class model generated two classes with insufficient membership, and failed the LRTs. Thus the conclusion was drawn that no acceptable model containing more than one class existed for the Self-Esteem dimension.

Locus of control. Estimation of growth with linear trajectories was optimal for the Locus of control models. Properties, fit statistics, and parameter estimates for these models are reported in Table 7. All of them failed to meet the stated criteria for model selection. The 2-class model, with minimal ICL-BIC and maximum entropy and classification probability, failed to provide a second class with adequate membership, where approximately 50 individuals is 1.5% of sample size. The 3-class model demonstrated minimal AIC, BIC, and ABIC, but resulted in unacceptably low entropy and classification probability. The 4-class model added a negligible class containing 4 individuals, and subsequently failed all three LRTs for significant improvement over the 3-class model.

Table 6. *Properties, Fit Statistics, and Parameter Estimates for Latent Growth Mixture Models of Self-Esteem*

	1-Class model	2-Class model	3-Class model	4-Class model
Sample size				
Class 1, N_{C1}	3078.00	3053.17	2125.82	2042.69
Class 2, N_{C2}		24.83	761.97	696.52
Class 3, N_{C3}			190.21	314.80
Class 4, N_{C4}				23.98
Fit statistics				
# Free parameters	14	18	19	23
Akaike's Information Criterion (AIC)	87743	87720	87701	87672
Schwarz's Bayesian Information Criterion (BIC)	87828	87829	87816	87811
Sample size adjusted BIC (ABIC)	87783	87771	87756	87738
Integrated Classification Likelihood (ICL-BIC)		87931	89886	90329
Entropy		.976	.694	.705
Average class membership posterior probability		.938	.826	.816
Vuong-Lo-Mendell-Rubin LRT, p		.0025	<.0001	.0183
Lo-Mendell-Rubin adjusted LRT, p		.0029	<.0001	.0202
Parametric bootstrap LRT (via 100 draws), p		<.0001	<.0001	<.0001

Table 6 (continued)

Latent variable means				
Class 1 intercept, γ_{01}	49.80 (0.15)	49.61 (0.15)	51.82 (0.34)	51.28 (0.41)
Class 1 linear slope, γ_{11}	-0.33 (0.13)	-0.21 (0.14) †	-0.75 (0.19)	-0.83 (0.19)
Class 1 quadratic slope, γ_{21}	0.08 (0.03)	0.06 (0.03)	0.13 (0.04)	0.15 (0.04)
Class 2 intercept, γ_{02}		73.07 (3.05)	40.62 (0.52)	40.06 (0.53)
Class 2 linear slope, γ_{12}		-15.72 (2.27)	1.34 (0.44)	1.67 (0.48)
Class 2 quadratic slope, γ_{22}		2.49 (0.52)	-0.08 (0.09) †	-0.13 (0.09) †
Class 3 intercept, γ_{03}			64.00 (1.53)	59.85 (1.10)
Class 3 linear slope, γ_{13}			-2.41 (1.01)	-0.60 (0.78†
Class 3 quadratic slope, γ_{33}			0.20 (0.19) †	-0.05 (0.17) †
Class 4 intercept, γ_{04}				75.76 (1.50)
Class 4 linear slope, γ_{14}				-12.54 (3.38)
Class 4 quadratic slope, γ_{24}				1.89 (0.61)
Latent variable variances and covariances				
Intercept, $\sigma^2\gamma_0$	35.34 (2.26)	31.10 (2.16)	0.00 [fixed]	0.00 [fixed]
Linear slope, $\sigma^2\gamma_1$	11.65 (1.76)	9.93 (1.84)	12.94 (1.32)	13.04 (1.38)
Quadratic slope, $\sigma^2\gamma_2$	0.36 (0.07)	0.31 (0.07)	0.41 (0.06)	0.42 (0.07)
Intercept by linear slope, $\sigma^2\gamma_0\sigma^2\gamma_1$	-4.34 (1.61)	-31.64 (1.62) †	0.00 [fixed]	0.00 [fixed]

Table 6 (continued)

Intercept by quadratic slope, $\sigma^2\gamma_0\sigma^2\gamma_2$	0.23 (0.29) †	-0.19 (0.30) †	0.00 [fixed]	0.00 [fixed]
Linear slope by quadratic slope, $\sigma^2\gamma_1\sigma^2\gamma_2$	-1.86 (0.34)	-1.59 (0.35)	0.00 [fixed]	0.00 [fixed]
Residual variances				
Academic year 1, σ^2_{e1}	38.39 (1.59)	38.27 (1.59)	37.72 (1.53)	35.80 (1.78)
Academic year 2, σ^2_{e2}	46.67 (1.97)	46.68 (1.96)	47.12 (1.98)	47.09 (1.99)
Academic year 3, σ^2_{e3}	38.39 (1.59)	38.27 (1.59)	37.72 (1.53)	35.80 (1.78)
Academic year 4, σ^2_{e4}	35.56 (1.93)	35.57 (1.93)	35.15 (1.92)	35.15 (1.91)
Academic year 5, σ^2_{e5}	34.41 (1.98)	34.46 (1.98)	34.33 (1.98)	34.52 (1.98)
Academic year 6, σ^2_{e6}	31.07 (3.74)	31.17 (3.73)	31.00 (3.68)	30.45 (3.66)

Note. LRT = Likelihood Ratio Test. All parameter estimates are significant statistically unless indicated by the † symbol. Parenthetical values are estimated standard errors.

Table 7. *Properties, Fit Statistics, and Parameter Estimates for Latent Growth Mixture Models of Locus of Control*

	1-Class model	2-Class model	3-Class model	4-Class model
Sample size				
Class 1, N_{C1}	3078.00	3028.28	2678.83	2675.35
Class 2, N_{C2}		49.72	246.87	244.48
Class 3, N_{C3}			152.30	153.78
Class 4, N_{C4}				4.39
Fit statistics				
# Free parameters	11	14	15	18
Akaike's Information Criterion (AIC)	85413	85407	85395	85397
Schwarz's Bayesian Information Criterion (BIC)	85480	85492	85485	85505
Sample size adjusted BIC (ABIC)	85480	85447	85438	85448
Integrated Classification Likelihood (ICL-BIC)		85821	87561	86555
Entropy		.923	.693	.754
Average class membership posterior probability		.847	.793	.809
Vuong-Lo-Mendell-Rubin LRT, *p*		.0083	<.0001	.1538†
Lo-Mendell-Rubin adjusted LRT, *p*		.0100	<.0001	.1640†
Parametric bootstrap LRT (via 100 draws), *p*		.0128	<.0001	.2857†

Table 7 (continued)

Latent variable means				
Class 1 intercept, γ_{01}	50.21 (0.13)	50.04 (0.16)	50.24 (0.27)	50.21 (0.27)
Class 1 linear slope, γ_{11}	0.24 (0.04)	0.30 (0.05)	0.17 (0.12) †	0.18 (0.12) †
Class 2 intercept, γ_{02}		60.70 (2.08)	45.34 (1.36)	45.32 (1.38)
Class 2 linear slope, γ_{12}		-4.00 (0.61)	3.06 (0.50)	3.07 (0.50)
Class 3 intercept, γ_{03}			57.60 (1.87)	57.85 (1.97)
Class 3 linear slope, γ_{13}			-3.16 (0.65)	-3.09 (0.64)
Class 4 intercept, γ_{04}				57.50 (3.51)
Class 4 linear slope, γ_{14}				-12.08 (2.74)
Latent variable variances and covariances				
Intercept, $\sigma^2\gamma_0$	35.55 (1.67)	33.72 (1.95)	31.07 (1.08)	31.00 (1.08)
Linear slope, $\sigma^2\gamma_1$	1.22 (0.15)	0.93 (0.16)	0.00 [fixed]	0.00 [fixed]
Intercept by linear slope, $\sigma^2\gamma_0\sigma^2\gamma_1$	-2.33 (0.43)	-1.59 (0.50)	0.00 [fixed]	0.00 [fixed]
Residual variances				
Academic year 1, σ^2_{e1}	37.05 (1.84)	37.15 (1.86)	37.02 (1.80)	36.87 (1.80)
Academic year 2, σ^2_{e2}	43.48 (1.90)	43.56 (1.91)	43.73 (1.90)	43.68 (1.90)

Table 7 (continued)

Academic year 3, σ^2_{e3}	36.81 (1.83)	36.78 (1.83)	36.75 (1.83)	36.38 (1.84)
Academic year 4, σ^2_{e4}	27.37 (1.42)	27.33 (1.41)	27.23 (1.41)	27.05 (1.41)
Academic year 5, σ^2_{e5}	22.97 (1.46)	22.89 (1.44)	23.27 (1.43)	23.33 (1.43)
Academic year 6, σ^2_{e6}	28.68 (2.52)	28.40 (2.46)	28.97 (2.28)	29.00 (2.28)

Note. LRT = Likelihood Ratio Test. All parameter estimates are significant statistically unless indicated by the † symbol. Parenthetical values are estimated standard errors.

Mastery motivation. Models including cubic growth estimates were found to be best fitting for the Mastery Motivation dimension. Properties, fit statistics, and parameter estimates for these models are reported in Table 8. While the 2-class model achieved minimal ICL-BIC and maximal entropy and average class membership posterior probability, it failed to provide a second class with sufficient membership. The 4-class model claimed the lowest AIC and ABIC, but also resulted in inadequate entropy and classification probability. Although it passed all likelihood ratio tests, models with additional classes continuously resulted in class sizes that were unacceptably small. The 3-class model was selected as the preferred solution, being the only model that met all stated criteria including classes of reasonable size, minimal if not the lowest values of fit statistics, and acceptable entropy and classification probability.

The estimated mean subpopulation trajectories for Mastery Motivation are presented in Figure 7. While all three classes start with mean intercepts near the population mean, their slopes over time differ widely. The quadratic and cubic slopes displayed nonsignificant variability within classes and were thus fixed to 0.0, indicating that student change trajectories within classes varied only linearly. The largest class of change trajectories, containing the extreme majority of students at 88.0%, was named the Regular class, with no particularly discernable curvature in trajectory. Although all components of the slope are statistically significant, they combine to form an effectively flat horizontal line where means at each timepoint never vary far from the population mean. Based on posterior membership estimates, 8.5% of the trajectories were classified into the Increasing-Decreasing class, where on average over time *SS*s first experience an

Table 8. *Properties, Fit Statistics, and Parameter Estimates for Latent Growth Mixture Models of Intrinsic Mastery Motivation*

	1-Class model	2-Class model	3-Class model	4-Class model
Sample size				
Class 1, N_{C1}	3078.00	3038.35	2709.20	2077.89
Class 2, N_{C2}		39.65	262.87	710.30
Class 3, N_{C3}			105.93	202.26
Class 4, N_{C4}				87.55
Fit statistics				
# Free parameters	16	21	23	28
Akaike's Information Criterion (AIC)	86295	86263	86250	86227
Schwarz's Bayesian Information Criterion (BIC)	86391	86390	86389	86396
Sample size adjusted BIC (ABIC)	86340	86323	86316	86307
Integrated Classification Likelihood (ICL-BIC)		86663	88364	90381
Entropy		.936	.708	.533
Average class membership posterior probability		.885	.819	.729
Vuong-Lo-Mendell-Rubin LRT, p		.0015	.0290	.0216
Lo-Mendell-Rubin adjusted LRT, p		.0018	.0312	.0236
Parametric bootstrap LRT (via 100 draws), p		<.0001	<.0001	<.0001

Table 8 (continued)

Latent variable means				
Class 1 intercept, γ_{01}	49.96 (0.15)	49.99 (0.16)	50.14 (0.22)	51.53 (0.53)
Class 1 linear slope, γ_{11}	-0.90 (0.25)	-1.06 (0.26)	-1.44 (0.41)	0.09 (0.56) †
Class 1 quadratic slope, γ_{21}	0.62 (0.13)	0.74 (0.13)	0.82 (0.17)	0.10 (0.24) †
Class 1 cubic slope, γ_{31}	-0.08 (0.02)	-0.10 (0.02)	-0.10 (0.02)	-0.02 (0.03) †
Class 2 intercept, γ_{02}		47.48 (3.25)	48.19 (1.38)	45.70 (1.22)
Class 2 linear slope, γ_{12}		11.27 (5.17)	3.46 (2.65) †	-5.17 (1.29)
Class 2 quadratic slope, γ_{22}		-9.20 (2.40)	0.48 (1.27) †	2.68 (0.54)
Class 2 cubic slope, γ_{32}		1.47 (0.30)	-0.28 (0.17) †	-0.30 (0.07)
Class 3 intercept, γ_{03}			49.76 (2.04)	48.92 (1.96)
Class 3 linear slope, γ_{13}			2.28 (4.86) †	1.38 (3.19) †
Class 3 quadratic slope, γ_{33}			-4.35 (2.78) †	1.48 (1.51) †
Class 3 cubic slope, γ_{33}			0.83 (0.39)	-0.41 (0.19)
Class 4 intercept, γ_{04}				49.29 (2.38)
Class 4 linear slope, γ_{14}				5.08 (4.16) †
Class 4 quadratic slope, γ_{24}				-5.84 (2.15)
Class 4 cubic slope, γ_{34}				1.03 (0.29)

Table 8 (continued)

Latent variable variances and covariances				
Intercept, $\sigma^2\gamma_0$	26.15 (1.58)	28.71 (2.28)	28.87 (1.77)	16.93 (4.25)
Linear slope, $\sigma^2\gamma_1$	0.00 [fixed]	3.89 (0.76)	1.42 (0.17)	1.19 (0.23)
Quadratic slope, $\sigma^2\gamma_2$	0.89 (0.17)	0.00 [fixed]	0.00 [fixed]	0.00 [fixed]
Cubic slope, $\sigma^2\gamma_3$	0.03 (0.01)	0.01 (0.00)	0.00 [fixed]	0.00 [fixed]
Intercept by linear slope, $\sigma^2\gamma_0\sigma^2\gamma_1$	0.00 [fixed]	-3.24 (1.19)	-2.62 (0.49)	-1.10 (0.89)*
Intercept by quadratic slope, $\sigma^2\gamma_0\sigma^2\gamma_2$	-0.68 (0.42) †	0.00 [fixed]	0.00 [fixed]	0.00 [fixed]
Intercept by cubic slope, $\sigma^2\gamma_0\sigma^2\gamma_3$	0.06 (0.08) †	0.02 (0.04) †	0.00 [fixed]	0.00 [fixed]
Linear slope by quadratic slope, $\sigma^2\gamma_1\sigma^2\gamma_2$	0.00 [fixed]	0.00 [fixed]	0.00 [fixed]	0.00 [fixed]
Linear slope by cubic slope, $\sigma^2\gamma_1\sigma^2\gamma_3$	0.00 [fixed]	-0.11 (0.03)	0.00 [fixed]	0.00 [fixed]
Quadratic slope by cubic slope, $\sigma^2\gamma_2\sigma^2\gamma_3$	-0.16 (0.03)	0.00 [fixed]	0.00 [fixed]	0.00 [fixed]
Residual variances				
Academic year 1, σ^2_{e1}	47.15 (1.80)	43.41 (2.36)	43.92 (2.14)	48.65 (2.43)
Academic year 2, σ^2_{e2}	46.31 (1.65)	46.50 (1.62)	46.82 (1.65)	44.01 (1.89)
Academic year 3, σ^2_{e3}	39.12 (1.62)	38.37 (1.64)	39.26 (1.73)	37.46 (1.71)
Academic year 4, σ^2_{e4}	30.27 (1.61)	29.82 (1.59)	29.78 (1.60)	30.27 (1.59)
Academic year 5, σ^2_{e5}	26.70 (1.66)	27.37 (1.63)	27.75 (1.61)	27.65 (1.58)
Academic year 6, σ^2_{e6}	21.38 (4.70)	16.41 (3.76)	14.56 (2.62)	14.90 (2.44)

Note. LRT = Likelihood Ratio Test. All parameter estimates are significant statistically unless indicated by the † symbol. Parenthetical values are estimated standard errors.

increase of approximately ¾ *SD* between Grades 7 and 10 before declining by nearly 1⅓ *SD* by Grade 12. In contrast, the 3.4% of change trajectories classified into the Decreasing-Increasing class experience an average decline of about 1 *SD* by Grade 10, with a cubic increase thereafter to reach an increment of 1½ *SD* in *SS* by Grade 12.

Note that slopes for one class (Increasing-Decreasing) in this model were also all nonsignificant, indicating that despite the curve drawn from the estimates of the slope components, the trajectory might be flat. Additionally, the quadratic component of the slope for the Decreasing-Increasing class was not significant at the .05 level, suggesting that the decrease over Grades 7-10 might not be reliable; instead, the slope for this class might be entirely a positive cubic, or increasing, relationship. As the quadratic slopes were insignificant for two of the three classes and its variance fixed, an attempt was made to remove this term from the model. The removal resulted in a model with three classes of trajectories shaped very similarly to those of the current model, with significant slopes but entropy of .63 and two failed LRTs. As further efforts at improving this model proved fruitless, subsequent analyses proceeded with the current model for exploratory aims, though great caution should be exercised in interpreting the results for any practical purpose.

Ancillary growth mixture models were estimated for the subsample of students with Mastery Motivation scores at all timepoints ($N = 1{,}158$). The resultant mean growth levels, distribution among classes, and random effects were all essentially the same as those for the full imputed sample, supporting the assumption that missing data were unrelated to levels or changes in the dependent variables (Little & Rubin, 2002; Marini, Olsen, & Rubin, 1979).

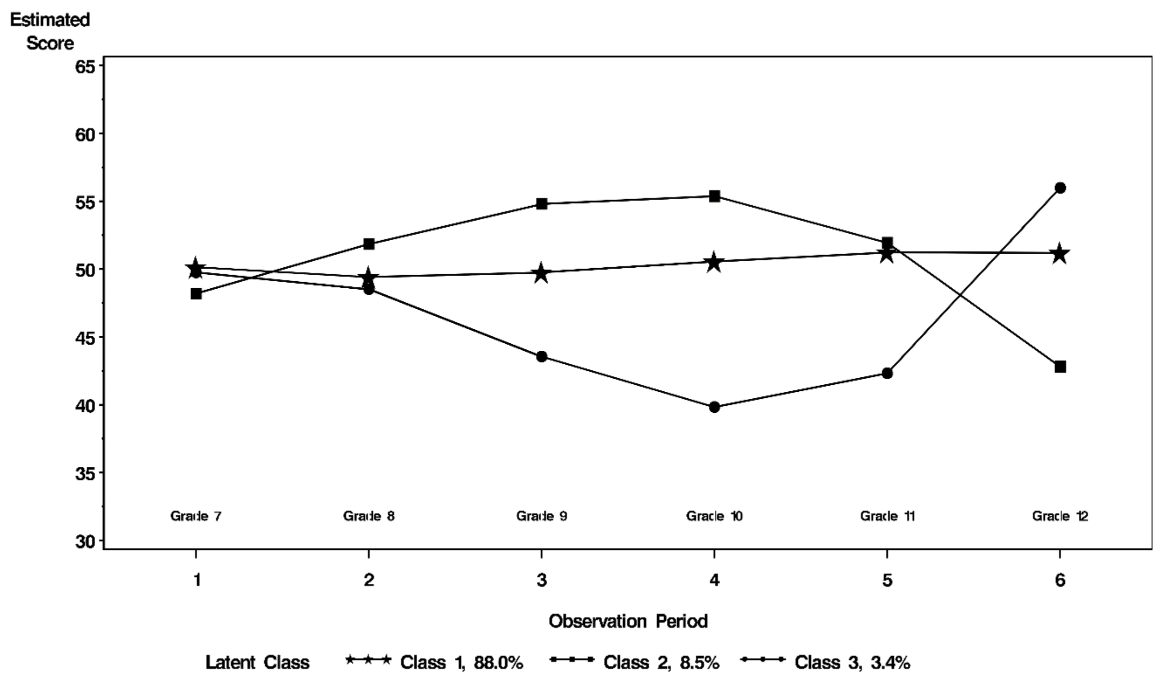

Figure 7. Estimated mean latent growth trajectories for Mastery Motivation.

Logistic Regression

As no reliable latent subpopulations were determined for either Self-Esteem or Locus of Control, the hypotheses related to distal outcomes could not be explored for those dimensions.

Figures 8.1 and 8.2 illustrate the relative probabilities of each distal achievement outcome associated with each latent growth class for Mastery Motivation. Bars with overlapping values indicate statistical nonsignificance, where probabilistic separation of classes is not evident for a particular outcome. For the most part the Decreasing-Increasing class appears indistinguishable from either of the other two classes in terms of probability of higher or lower science achievement, with the exception of having a probability near zero of being in the highest standardized test quintile. Note however that this is not matched by a higher probability of being in the lowest quintile. The Increasing-Decreasing class, in comparison to the Regular class, demonstrates statistically significantly lower probabilities of taking an advanced science course by Grade 12, having higher science standardized test achievement and having higher average science course grades.

Figure 9 illustrates the relative probabilities of each distal college outcome associated with each latent growth class for Mastery Motivation. In general it appears that membership in the Increasing-Decreasing class has a negative association with distal college outcomes. Membership in that class is associated with lower probabilities of attaining a BA, graduating with a STEM degree, and having a graduate major in STEM. Although the Decreasing-Increasing class has a slightly larger probability of starting a STEM major than either class according to its point estimate, this effect is not statistically significant.

Figure 10 illustrates the relative probabilities of each distal career outcome associated with each latent growth class for Mastery Motivation. Aside from the Increasing-Decreasing class being less likely than the Regular class to be engaged in a current STEM career, there is no probabilistic separation between classes.

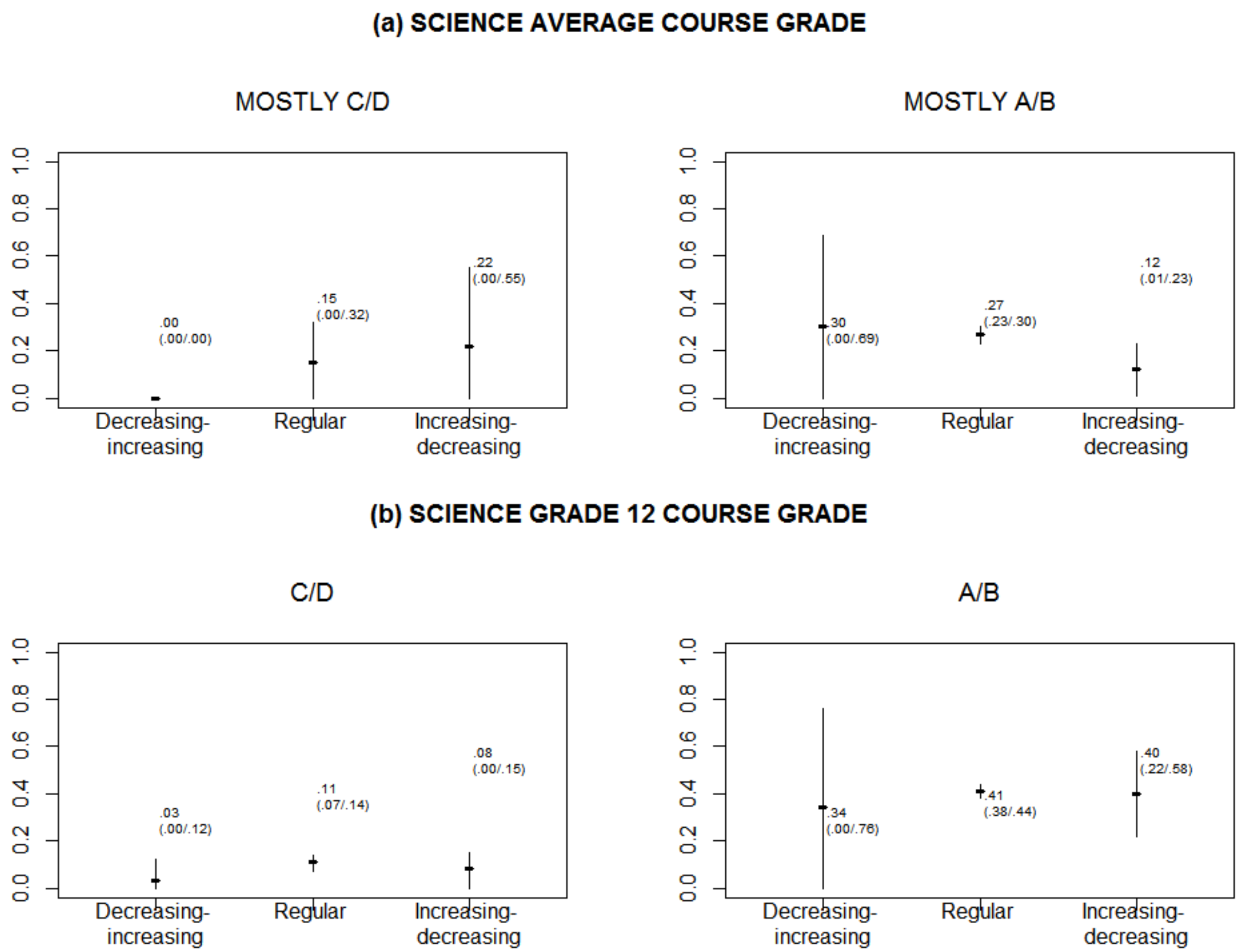

Figure 8.1. Predicted mean probability (and 95% confidence bands) of achievement outcomes (course grades) associated with membership in latent classes of Mastery Motivation.

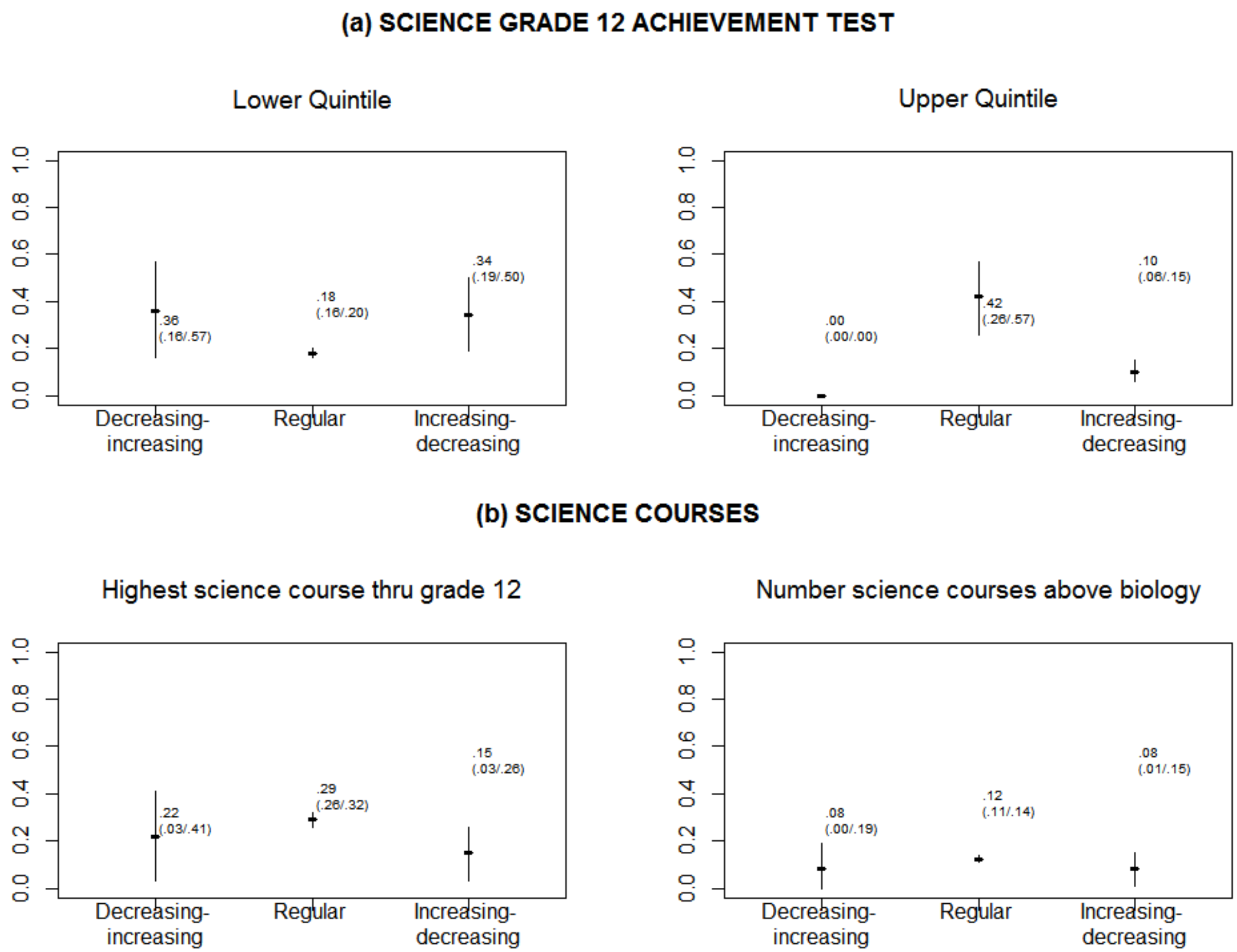

Figure 8.2. Predicted mean probability (and 95% confidence bands) of achievement outcomes (standardized science test and advanced science coursework) associated with membership in latent classes of Mastery Motivation.

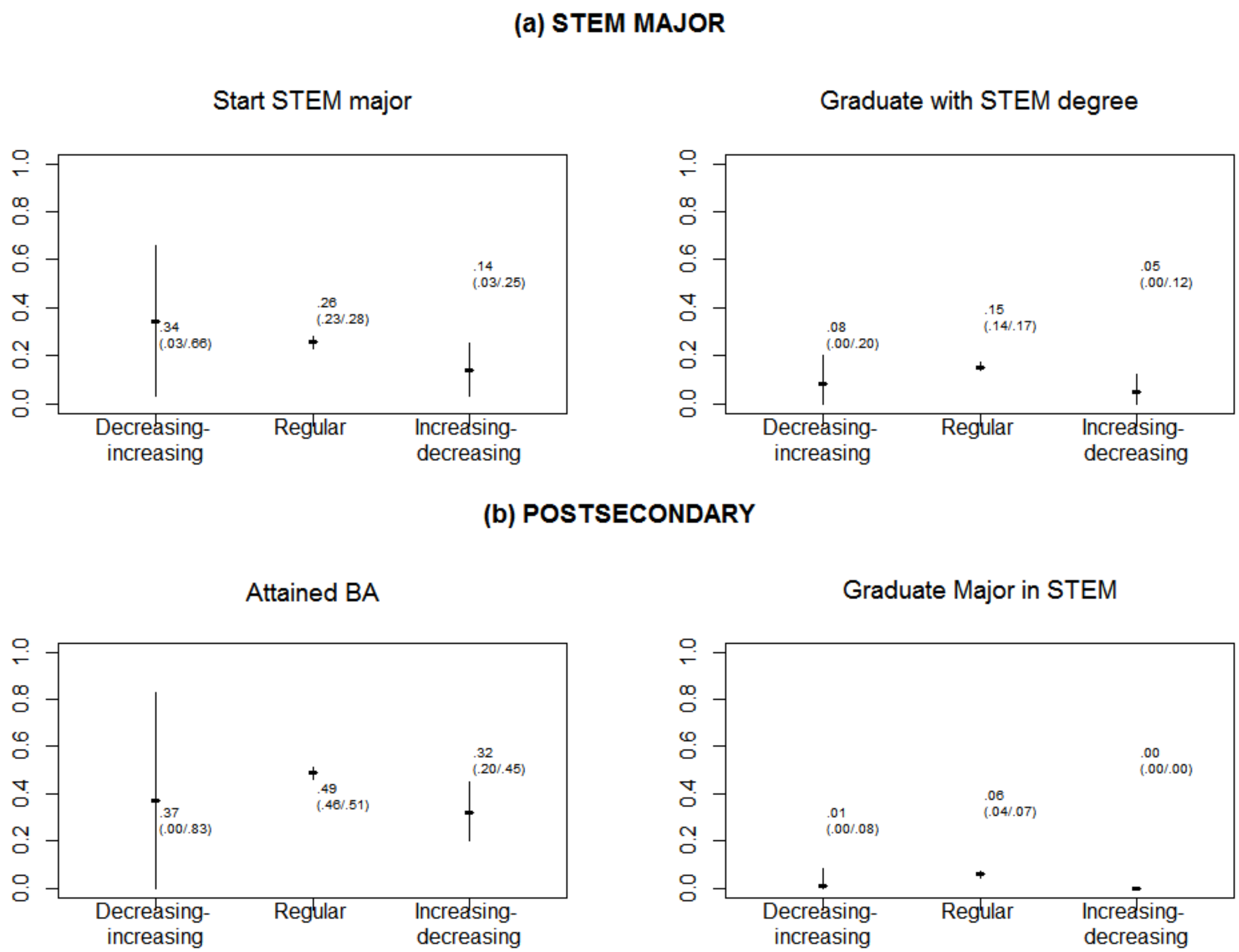

Figure 9. Predicted mean probability (and 95% confidence bands) of college outcomes associated with membership in latent classes of Mastery Motivation.

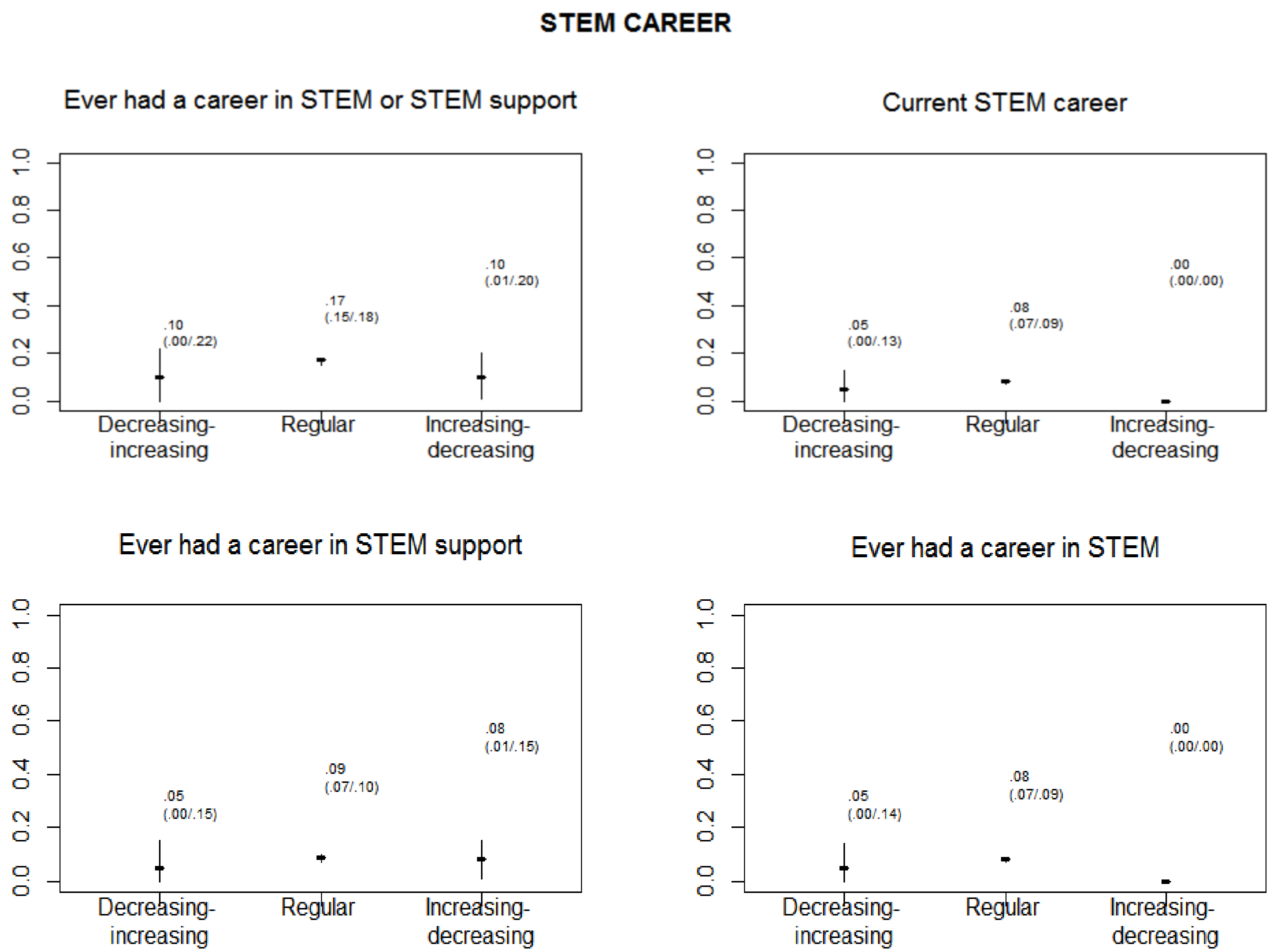

Figure 10. Predicted mean probability (and 95% confidence bands) of career outcomes associated with membership in latent classes of Mastery Motivation.

Multinomial Logistic Regression

As no reliable latent subpopulations were determined for either Self-Esteem or Locus of Control, the hypotheses related to explanatory covariates could not be explored for those dimensions. None of the potential explanatory covariates were significant for Mastery Motivation.

Attitudes toward Science

Descriptive statistics indicating central tendency, dispersion, and distribution were calculated for all attitudes toward science items. Skewness and kurtosis were within the acceptable range of -1 to 1 for approximately normal distributions for all items, with the exception of ‘positive attitude toward self’ where both skewness and kurtosis were greater than 1 but less than 1.5, and ‘able to do things as well as others’ where kurtosis was greater than 1 but less than 1.5. All correlations were in the expected directions.

Dimensionality

MAP for the10 items pertaining to attitudes toward science suggested that a minimum of 2 factors might be extracted from the smoothed polychoric correlation matrix. Models containing 1, 2, 3, and 4 factors were assessed against the stated criteria. The 2-factor model was selected as the optimal solution. The 1-factor model compressed items into a less distinct and comprehensible composite and models featuring greater than 2 factors proved unreliable. Three items loaded on both dimensions, with a factor intercorrelation of -.38.

Table 9 displays rotated pattern loadings, final communalities, product-moment item-scale correlations, and coefficients α (as a lower bound) and ω_t (as a higher bound)

Table 9. *Dimensional Structure and Properties of the Attitudes toward Science Measure*

Item description[a]	Scale pattern loadings[b] I	Scale pattern loadings[b] II	Commu-nality	Item/ scale r^c
Science Utility (coefficient α = .86, ω_t = .88) [d]				
Science useful in everyday problems	*.81*	.06	.62	.70
Science helps logical thinking	*.77*	.07	.55	.66
Need science for a good job	*.74*	.06	.52	.64
Will use science often as an adult	*.72*	.00	.51	.66
I enjoy science	*.59*	*-.37*	.65	.73
I am good at science	*.49*	*-.53*	.72	.74
I usually understand science	*.44*	*-.56*	.69	.70
Science Self-Concept (coefficient α = .77, ω_t = .77) [d]				
Scared when I open science book (r)	.15	*.73*	.47	.54
Science makes me nervous (r)	.00	*.72*	.52	.66
I usually understand science	.44	*-.56*	.69	.75
I am good at science	.49	*-.53*	.72	.76
Worry about science test grades (r)	.12	*.44*	.17	.31
I enjoy science	.59	*-.37*	.65	.65

[a]Item descriptions are abbreviated for convenient presentation.
[b]Values are promaxian pattern loadings. Salient pattern loadings ($\geq .35$) are italicized.
[c]Each correlation reflects the relationship between an item and the sum of the other items comprising a scale, where distributions were standardized to unit-normal form.
[d]Reliability is based on the sample $N = 420$

for each scale. Based on patterns of descending loadings and item content, the scales were named Science Utility (7 items) and Science Self-Concept (6 items).

The two-dimensional structure was validated with the confirmatory subsample. Model fit was adequate with $\chi 2$ (31) = 89.537, CFI = .935, and RMSEA = .067 (90% CI = .051-.084).

Longitudinal Measurement Invariance

Attitudinal dimensions were determined to be appropriately invariant across time. As with the self-evaluation dimensions, chi-square tests were significant but otherwise all other fit criteria were met for configural, metric, and scalar invariance. Model fit statistics and associated decrements are displayed in Table 10.

Table 10. *Measurement Invariance for Attitudes toward Science*

Model	CFI	ΔCFI	RMSEA	ΔRMSEA
Configural	.910	---	.040	---
Metric	.910	.000	.039	.001
Scalar	.901	.009	.040	.001
Equal residuals	.894	.007	.041	.001

Scaling

AIC and BIC values for both dimensions suggested that the graded response model was a better fit to the data than the generalized partial credit model. The graded response threshold parameters for Science Utility ranged -1.59-2.50 (M = 0.58, SD = 1.26) and slopes 1.42-2.65 (M = 1.97, SD = 0.44); the response threshold parameters for Science Self-Concept ranged -13.12-6.35 (M = 0.01, SD = 3.54) and slopes 0.18-4.42 (M

= 2.00, *SD* = 1.47). EAP (Thissen et al., 1995) scaled scores for each dimension were produced, with *M* = 50 and *SD* = 10 and higher scores indicating more positive attitudes toward utility of science and individual science efficacy. The scales were internally consistent with Science Utility yielding an α coefficient of .86 and Science Self-Concept an α coefficient of .77. Marginal reliability for response pattern scores was .88 and .87, respectively. Both dimensions exhibited some evidence of convergent validity by reasonable correlation with measures of class-specific utility for Science Utility (about .40) and liking the subject for Science Self-Concept (about .50) at timepoint 1 (Grade 7). See Figures 11 and 12 for overlay plots of test information functions and standard error curves.

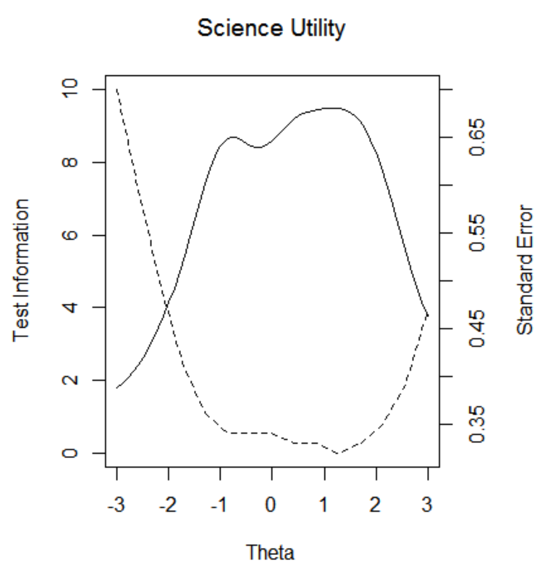

Figure 11. Distributions of estimated information functions and standard errors for Science Utility scale

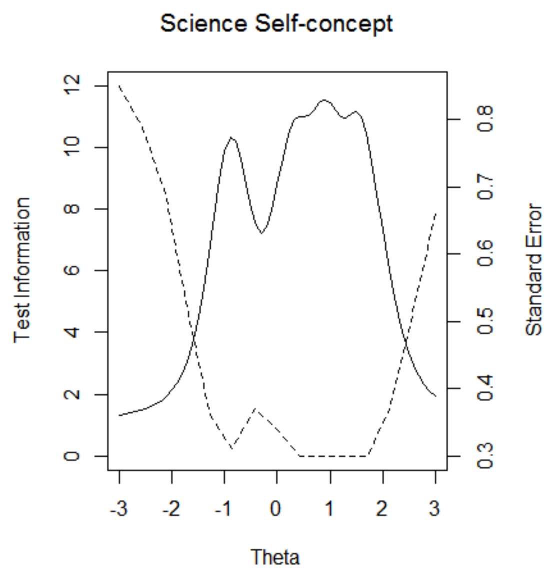

Figure 12. Distributions of estimated information functions and standard errors for Science Self-Concept scale

Latent Growth Mixture Models

Models using polynomial growth estimates were uniformly better fitting than those estimated using latent basis estimation. Estimation of growth including cubic trajectories was optimal for both attitudinal dimensions. Results of models are reported below.

Science utility. Properties, fit statistics, and parameter estimates for Science Utility models are reported in Table 11. The 4-class model achieved minimal AIC, BIC, and ABIC, but failed two of the three likelihood ratio tests that would indicate significant improvement over a model with one less class. The 2-class model, while exhibiting the lowest ICL-BIC and highest entropy, failed to provide a class meeting the stated minimum class size. The 3-class model was thus selected as the preferred model, having met all stated criteria and demonstrating adequate fit overall.

The estimated mean subpopulation trajectories for Science Utility are presented in Figure 13. The quadratic slope variance within classes was consistently found to be nonsignificant and so fixed to zero in all models. For the 3-class model, the linear slope also demonstrated nonsignificant variability; the cubic slope variance, though significant, had a value of less than .005. Of the three classes, one was distinctly dominant, containing 86.4% of trajectories. As the slope components combined to result in a horizontal line with an extremely slight upward trend, this class was named the Regular class. Based on posterior membership classifications, the next largest class was the Increasing class, representing 8.3% of trajectories, with the Decreasing-Increasing class smallest at 5.3%. The Increasing class of trajectories on average starts with an *SS* lower than the population mean, though experiences a positive increase of 1 *SD* between Grades 7 and 8, another ½ *SD* by grade 9, and plateaus thereafter. The Decreasing-Increasing class experiences a bit of the opposite, where the mean intercept is more than 1 *SD* above the population mean, but decreases by 1 *SD* by Grade 8 and another ½ *SD* by Grade 10 before curving upward for an increment of ½ *SD* at Grade 12.

To check the assumption that missing data was unrelated to change in the dependent variables, ancillary growth mixture models were estimated for the subsample of students with Science Utility scores at all timepoints (N = 1,086). The resultant mean growth levels, patterns, and random effects were all quite similar to those for the full FIML-imputed sample.

Table 11. *Properties, Fit Statistics, and Parameter Estimates for Latent Growth Mixture Models of Attitude toward Utility of Science*

	1-Class model	2-Class model	3-Class model	4-Class model
Sample size				
Class 1, N_{C1}	3062.00	2975.77	2646.06	2483.10
Class 2, N_{C2}		86.23	254.44	235.09
Class 3, N_{C3}			161.51	229.19
Class 4, N_{C4}				114.63
Fit statistics				
# Free parameters	14	20	22	27
Akaike's Information Criterion (AIC)	86137	86046	86012	85964
Schwarz's Bayesian Information Criterion (BIC)	86222	86167	86145	86127
Sample size adjusted BIC (ABIC)	86177	86103	86075	86041
Integrated Classification Likelihood (ICL-BIC)		86541	87571	88105
Entropy		.912	.788	.767
Average class membership posterior probability		.878	.833	.789
Vuong-Lo-Mendell-Rubin LRT, *p*		.0258	<.0000	.1564†
Lo-Mendell-Rubin adjusted LRT, *p*		.0279	<.0000	.1646†
Parametric bootstrap LRT (via 100 draws), *p*		<.0001	<.0001	<.0001

Table 11 (continued)

Latent variable means				
Class 1 intercept, γ_{01}	50.02 (0.17)	50.33 (0.20)	50.48 (0.26)	51.40 (0.30)
Class 1 linear slope, γ_{11}	0.11 (0.27) †	-0.74 (0.31)	-0.63 (0.37) †	0.16 (0.39) †
Class 1 quadratic slope, γ_{21}	0.21 (0.14) †	0.57 (0.15)	0.53 (0.16)	0.13 (0.19) †
Class 1 cubic slope, γ_{31}	-0.03 (0.02)	-0.07 (0.02)	-0.07 (0.02)	-0.03 (0.02) †
Class 2 intercept, γ_{02}		39.14 (2.44)	37.49 (1.22)	35.65 (0.97)
Class 2 linear slope, γ_{12}		31.80 (3.67)	17.75 (2.48)	16.91 (2.68)
Class 2 quadratic slope, γ_{22}		-13.54 (2.03)	-5.41 (1.23)	-5.04 (1.34)
Class 2 cubic slope, γ_{32}		1.64 (0.27)	0.51 (0.16)	0.49 (0.17)
Class 3 intercept, γ_{03}			62.10 (1.99)	41.77 (1.68)
Class 3 linear slope, γ_{13}			-14.86 (2.42)	-9.48 (2.41)
Class 3 quadratic slope, γ_{33}			3.48 (1.21)	4.55 (1.04)
Class 3 cubic slope, γ_{33}			-0.20 (0.16) †	-0.48 (0.13)
Class 4 intercept, γ_{04}				65.88 (2.91)
Class 4 linear slope, γ_{14}				-14.82 (3.36)
Class 4 quadratic slope, γ_{24}				3.19 (1.72)
Class 4 cubic slope, γ_{34}				-0.18 (0.23) †

Table 11 (continued)

Latent variable variances and covariances				
Intercept, $\sigma^2\gamma_0$	36.31 (1.69)	51.04 (3.02)	40.41 (1.90)	26.84 (3.13)
Linear slope, $\sigma^2\gamma_1$	3.14 (0.54)	6.94 (0.95)	0.00 [fixed]	0.00 [fixed]
Quadratic slope, $\sigma^2\gamma_2$	0.00 [fixed]	0.00 [fixed]	0.00 [fixed]	0.00 [fixed]
Cubic slope, $\sigma^2\gamma_3$	0.00 (0.00)	0.01 (0.00)	0.00 (0.00)	0.00 (0.00)
Intercept by linear slope, $\sigma^2\gamma_0\sigma^2\gamma_1$	0.00 [fixed]	-8.20 (1.53)	0.00 [fixed]	0.00 [fixed]
Intercept by quadratic slope, $\sigma^2\gamma_0\sigma^2\gamma_2$	0.00 [fixed]	0.00 [fixed]	0.00 [fixed]	0.00 [fixed]
Intercept by cubic slope, $\sigma^2\gamma_0\sigma^2\gamma_3$	-0.12 (0.02)	0.13 (0.05)	-0.09 (0.02)	0.01 (0.03)*
Linear slope by quadratic slope, $\sigma^2\gamma_1\sigma^2\gamma_2$	0.00 [fixed]	0.00 [fixed]	0.00 [fixed]	0.00 [fixed]
Linear slope by cubic slope, $\sigma^2\gamma_1\sigma^2\gamma_3$	-0.08 (0.02)	-0.20 (0.03)	0.00 [fixed]	0.00 [fixed]
Quadratic slope by cubic slope, $\sigma^2\gamma_2\sigma^2\gamma_3$	0.00 [fixed]	0.00 [fixed]	0.00 [fixed]	0.00 [fixed]
Residual variances				
Academic year 1, σ^2_{e1}	51.73 (2.24)	33.29 (3.69)	27.59 (3.03)	30.47 (2.94)
Academic year 2, σ^2_{e2}	53.57 (2.53)	51.76 (2.67)	54.15 (2.59)	53.18 (2.76)
Academic year 3, σ^2_{e3}	42.04 (1.85)	40.48 (1.80)	41.83 (1.83)	42.24 (2.00)
Academic year 4, σ^2_{e4}	42.04 (1.85)	40.48 (1.80)	41.83 (1.83)	42.24 (2.00)
Academic year 5, σ^2_{e5}	29.65 (2.33)	29.45 (2.37)	32.09 (2.37)	32.06 (2.36)
Academic year 6, σ^2_{e6}	17.78 (4.10)	10.91 (4.27)	12.03 (3.40)	16.77 (3.60)

Note. LRT = Likelihood Ratio Test. All parameter estimates are significant statistically unless indicated by the † symbol. Parenthetical values are estimated standard errors.

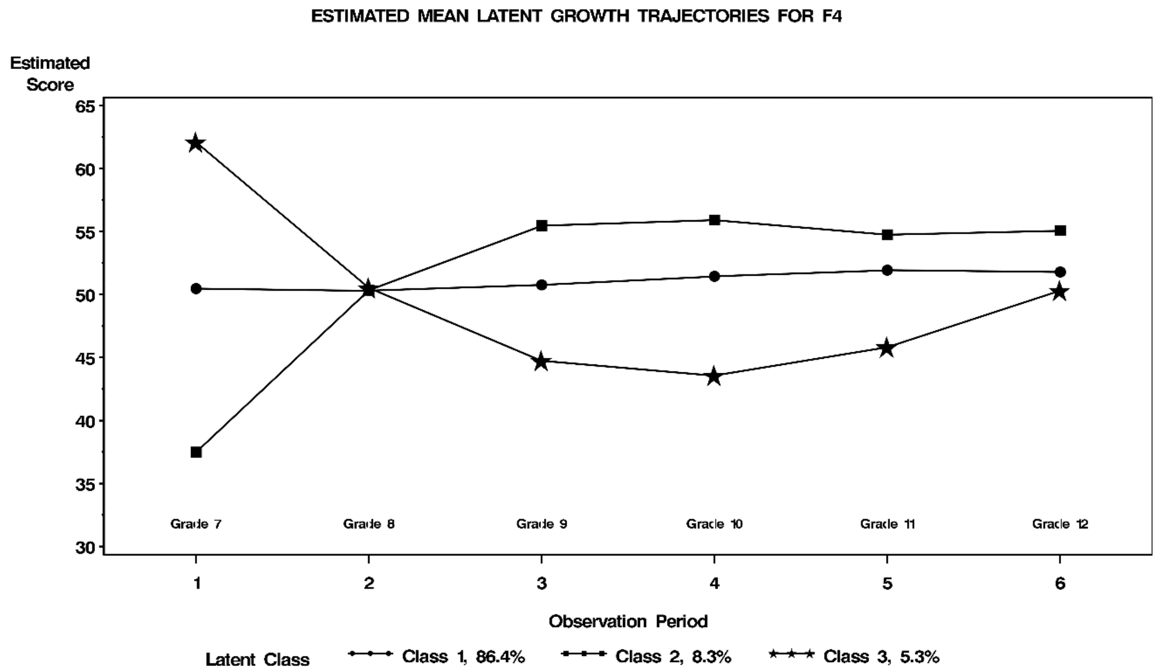

Figure 13. Estimated mean latent growth trajectories for Science Utility.

Science self-concept. Properties, fit statistics, and parameter estimates for Science Self-Concept models are reported in Table 12. The 5-class model met minimal AIC, BIC, and ABIC, but failed two of the three likelihood ratio tests. The 2-class model exhibited low entropy, while the 4-class model proved just shy of the ideal average classification probability ≥ .800 at .799. Additionally, the 3-class model demonstrated the minimal value for ICL-BIC and quite good fit on all other grounds, making it the preferable model.

Estimated mean latent growth trajectories for Science Self-Concept classes are presented in Figure 14. As in the Science Utility model and the Mastery Motivation model, there is one class containing the majority of trajectories which manifests an average trajectory of a horizontal line, in this case very slightly increasing, near the population mean. As in the other two models, this is deemed the Regular class. Posterior membership estimates classify 18.6% of trajectories into the Decreasing class, and 12.3% into the Increasing class. The Decreasing class starts with an average *SS* almost 1½ *SD* above the population mean, but experiences an early decrease of approximately 1 *SD* by Grade 8. From Grade 8 there is a much less steep decrease to Grade 9, with a plateau and slight increase thereafter. Interestingly, the mean *SS* for this class remains above the Regular class at all timepoints. For the Increasing class, a negative quadratic slope and a positive cubic slope result in an initial sharp increase between Grades 7 and 9 covering about 1 *SD*, and then a much slighter increase of less than ½ *SD* cumulatively from Grade 9 up to Grade 12. Notably the mean *SS* for this class is consistently below that of the regular class, even when demonstrating marked increase. However it also starts with a mean intercept 1½ *SD* below the population mean.

The subsample of students with Science Self-Concept scores at all timepoints (*N* = 1,086) was submitted to a series of ancillary growth mixture models. Inspection of the mean growth levels, distributions, and random effects supported the assumption that missing data was missing at random, as they were a close match to the parameters produced by the full imputed sample.

Table 12. *Properties, Fit Statistics, and Parameter Estimates for Latent Growth Mixture Models of Attitude toward Science Self-Concept*

	1-Class model	2-Class model	3-Class model	4-Class model	5-Class model
Sample size					
Class 1, N_{C1}	3062.00	2513.71	2116.44	2108.98	2030.79
Class 2, N_{C2}		548.29	568.13	370.77	350.96
Class 3, N_{C3}			377.43	341.62	318.83
Class 4, N_{C4}				240.64	267.12
Class 5, N_{C5}					94.30
Fit statistics					
# Free parameters	16	21	26	31	36
Akaike's Information Criterion (AIC)	85386	85345	85193	85143	85103
Schwarz's Bayesian Information Criterion (BIC)	85482	85472	85350	85330	85320
Sample size adjusted BIC (ABIC)	85431	85405	85267	85232	85206
Integrated Classification Likelihood (ICL-BIC)		87131	86810	87283	87626
Entropy		.609	.783	.770	.766
Average class membership posterior probability		.835	.884	.799	.781

Table 12 (continued)

Vuong-Lo-Mendell-Rubin LRT, *p*		.0064	<.0000	.0036	.1239†
Lo-Mendell-Rubin adjusted LRT, *p*		.0072	<.0000	.0041	.1297†
Parametric bootstrap LRT (via 100 draws), *p*		<.0000	<.0000	<.0000	<.0000
Latent variable means					
Class 1 intercept, γ_{01}	49.98 (0.17)	51.85 (0.46)	51.34 (0.27)	51.42 (0.26)	51.47 (0.26)
Class 1 linear slope, γ_{11}	-0.09 (0.26)	0.45 (0.39) †	-0.74 (0.37)	-0.77 (0.38)	-0.05 (0.45) †
Class 1 quadratic slope, γ_{21}	0.30 (0.13)	-0.01 (0.18) †	0.52 (0.18)	0.50 (0.19)	0.22 (0.21) †
Class 1 cubic slope, γ_{31}	-0.04 (0.02)	0.00 (0.02) †	-0.06 (0.02)	-0.06 (0.03)	-0.03 (0.03) †
Class 2 intercept, γ_{02}		41.34 (0.86)	35.88 (0.26)	63.81 (0.79)	64.08 (0.80)
Class 2 linear slope, γ_{12}		-2.52 (1.58) †	9.85 (0.90)	-13.08 (1.94)	-12.97 (1.95)
Class 2 quadratic slope, γ_{22}		1.67 (0.57)	-2.77 (0.46)	4.70 (1.05)	4.82 (1.08)
Class 2 cubic slope, γ_{32}		-0.19 (0.07)	0.27 (0.06)	-0.49 (0.14)	-0.52 (0.14)
Class 3 intercept, γ_{03}			63.71 (0.83)	35.47 (0.28)	35.53 (0.32)
Class 3 linear slope, γ_{13}			-11.71 (1.70)	3.81 (1.75)	2.82 (1.40)
Class 3 quadratic slope, γ_{33}			3.89 (0.91)	-0.00 (0.75) †	0.23 (0.59) †
Class 3 cubic slope, γ_{33}			-0.38 (0.12)	-0.06 (0.09) †	-0.07 (0.08) †
Class 4 intercept, γ_{04}				36.88 (0.70)	36.74 (0.61)
Class 4 linear slope, γ_{14}				19.80 (2.58)	19.25 (2.23)
Class 4 quadratic slope, γ_{24}				-7.53 (1.44)	-7.11 (1.27)
Class 4 cubic slope, γ_{34}				0.86 (0.19)	0.79 (0.17)

Table 12 (continued)

Class 5 intercept, γ_{05}					52.19 (2.49)
Class 5 linear slope, γ_{15}					-19.22 (3.89)
Class 5 quadratic slope, γ_{25}					7.07 (1.76)
Class 5 cubic slope, γ_{35}					-0.65 (0.21)
Latent variable variances and covariances					
Intercept, $\sigma^2\gamma_0$	49.03 (3.23)	20.56 (4.14)	12.02 (3.56)	16.15 (4.07)	17.55 (3.75)
Linear slope, $\sigma^2\gamma_1$	12.26 (2.11)	0.00 [fixed]	4.58 (1.13)	5.50 (1.22)	4.72 (1.17)
Quadratic slope, $\sigma^2\gamma_2$	0.38 (0.07)	1.03 (0.20)	0.00 [fixed]	0.00 [fixed]	0.00 [fixed]
Cubic slope, $\sigma^2\gamma_3$	0.00 [fixed]	0.03 (0.01)	0.01 (0.00)	0.01 (0.00)	0.01 (0.00)
Intercept by linear slope, $\sigma^2\gamma_0\sigma^2\gamma_1$	-11.47 (2.38)	0.00 [fixed]	0.71 (1.88) †	-1.86 (2.13) †	-3.50 (2.03) †
Intercept by quadratic slope, $\sigma^2\gamma_0\sigma^2\gamma_2$	1.28 (0.40)	-1.69 (0.90)	0.00 [fixed]	0.00 [fixed]	0.00 [fixed]
Intercept by cubic slope, $\sigma^2\gamma_0\sigma^2\gamma_3$	0.00 [fixed]	0.29 (0.17)	-0.04 (0.05) †	0.03 (0.06) †	0.08 (0.06) †
Linear slope by quadratic slope, $\sigma^2\gamma_1\sigma^2\gamma_2$	-1.97 (0.38)	0.00 [fixed]	0.00 [fixed]	0.00 [fixed]	0.00 [fixed]
Linear slope by cubic slope, $\sigma^2\gamma_1\sigma^2\gamma_3$	0.00 [fixed]	0.00 [fixed]	-0.14 (0.04)	-0.17 (0.04)	-0.12 (0.04)
Quadratic slope by cubic slope, $\sigma^2\gamma_2\sigma^2\gamma_3$	0.00 [fixed]	-0.18 (0.04)	0.00 [fixed]	0.00 [fixed]	0.00 [fixed]
Residual variances					
Academic year 1, σ^2_{e1}	38.25 (3.06)	50.72 (2.29)	13.59 (3.94)	9.14 (3.93)	7.76 (3.58)
Academic year 2, σ^2_{e2}	45.51 (1.82)	42.38 (2.19)	51.71 (1.89)	49.13 (1.99)	46.85 (2.26)
Academic year 3, σ^2_{e3}	42.40 (1.98)	43.53 (2.10)	43.89 (1.96)	41.83 (1.98)	40.88 (2.06)

Table 12 (continued)

Academic year 4, σ^2_{e4}	37.18 (1.99)	37.19 (2.07)	35.80 (2.04)	36.04 (2.03)	36.98 (2.06)
Academic year 5, σ^2_{e5}	31.16 (1.88)	29.38 (2.00)	30.86 (1.94)	30.71 (1.97)	30.70 (1.99)
Academic year 6, σ^2_{e6}	21.23 (3.42)	19.71 (5.59)	19.31 (4.25)	16.34 (4.56)	19.82 (4.89)

Note. LRT = Likelihood Ratio Test. All parameter estimates are significant statistically unless indicated by the † symbol. Parenthetical values are estimated standard errors.

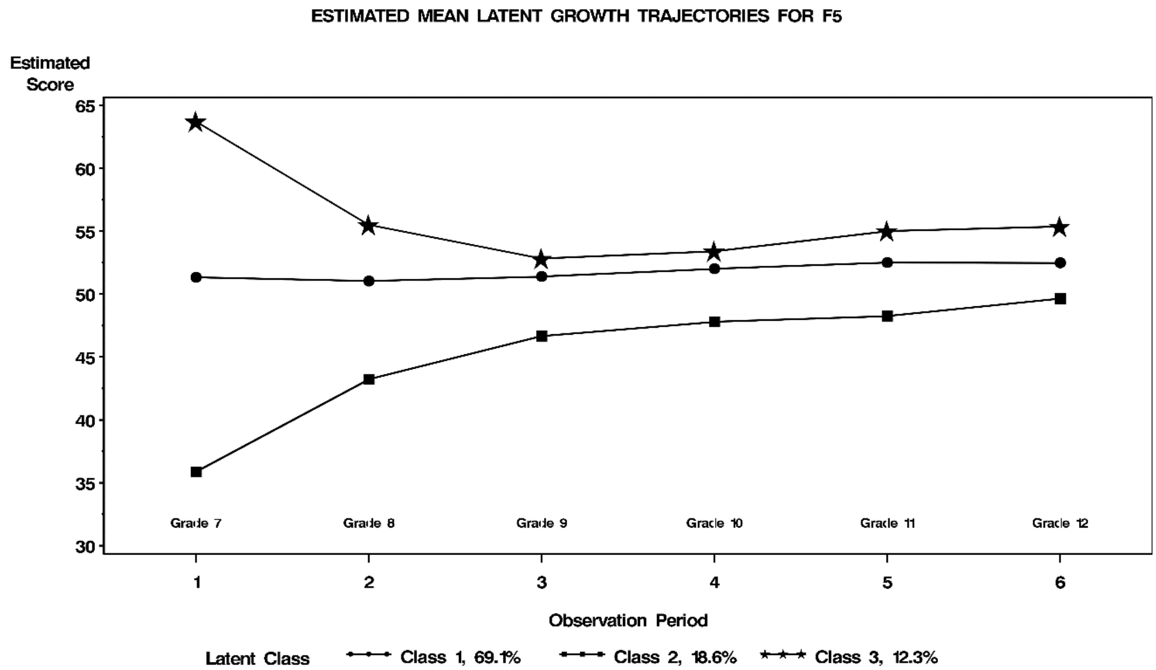

Figure 14. Estimated mean latent growth trajectories for Science Self-Concept.

Logistic Regression

Science utility. Figures 15.1 and 15.2 illustrate the relative probabilities of each distal achievement outcome associated with each latent growth class for Science Utility. By point estimate it appears as though the Decreasing-Increasing class is slightly more likely than members of either other class to enroll in an above average number of science courses above biology, to be in the highest quintile for the standardized science test, and to have a Grade 12 science course grade in the A-B range. However, the overlapping error bars indicate that these associations are not statistically significant. The only achievement outcomes where probabilistic separation of classes is evident are those related to average science course grades, where the Regular class is far more likely to achieve an A-B average than both the Increasing class and the Decreasing-Increasing class, and far less likely to have an average in the below C range. As the average science course grades were calculated by averaging science course grades across years, this does not contradict any of the other results and makes sense insofar as the change trajectories for both the Decreasing-Increasing class and the Increasing class clearly indicated movement where the Regular class was fairly constant.

Figure 16 illustrates the relative probabilities of each distal college outcome associated with each latent growth class for Science Utility. Although the point estimates here indicate that members of the Decreasing-Increasing class are more likely (and members of the Increasing class less likely) to start a STEM major, graduate with a STEM degree, and have a graduate major in STEM, these effects are not statistically significant, making them inconclusive. There appears to be no reliable separation of classes in terms of probabilities of college outcomes.

Figure 17 illustrates the relative probabilities of each distal career outcome associated with each latent growth class for Science Utility. As with the other outcomes, there are some indications in point estimates that membership in the Decreasing-Increasing class is associated with more engagement in STEM careers, but the overlap in error bands suggests that this is not significant. Thus class membership appears to have no differential association with the probability of an eventual STEM career.

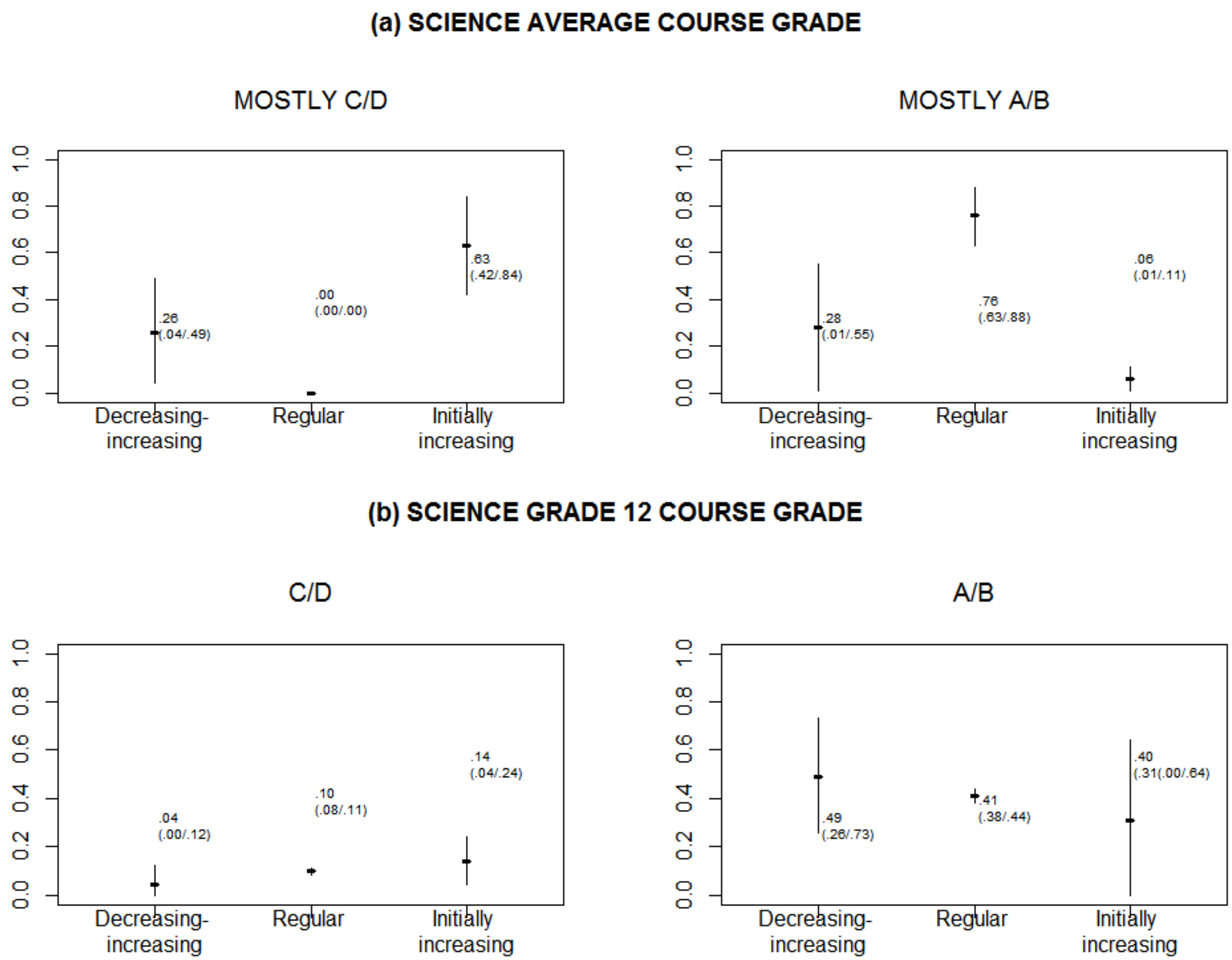

Figure 15.1. Predicted mean probability (and 95% confidence bands) of achievement outcomes (course grades) associated with membership in latent classes of Science Utility.

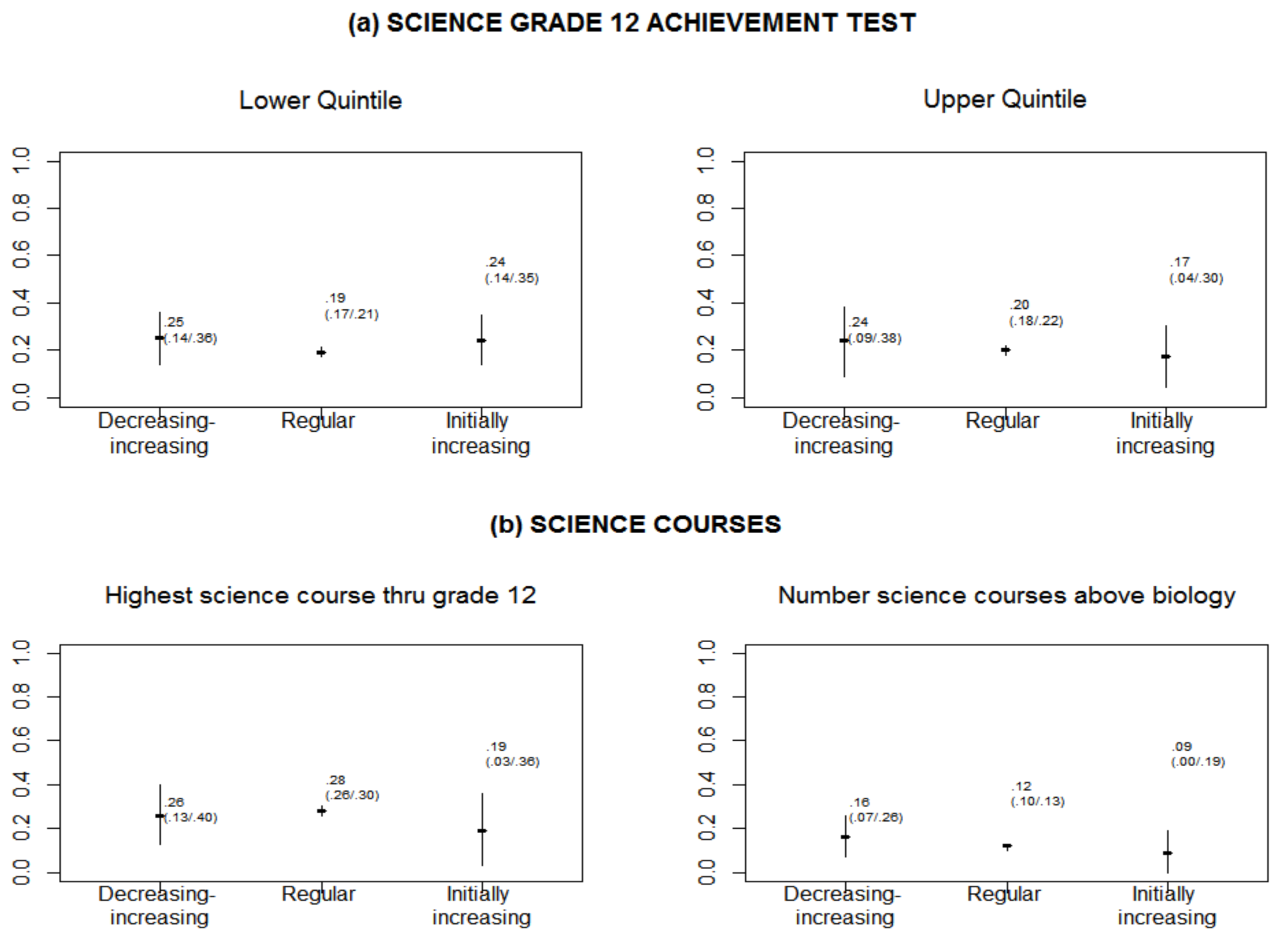

Figure 15.2. Predicted mean probability (and 95% confidence bands) of achievement outcomes (standardized science test and advanced science coursework) associated with membership in latent classes of Science Utility.

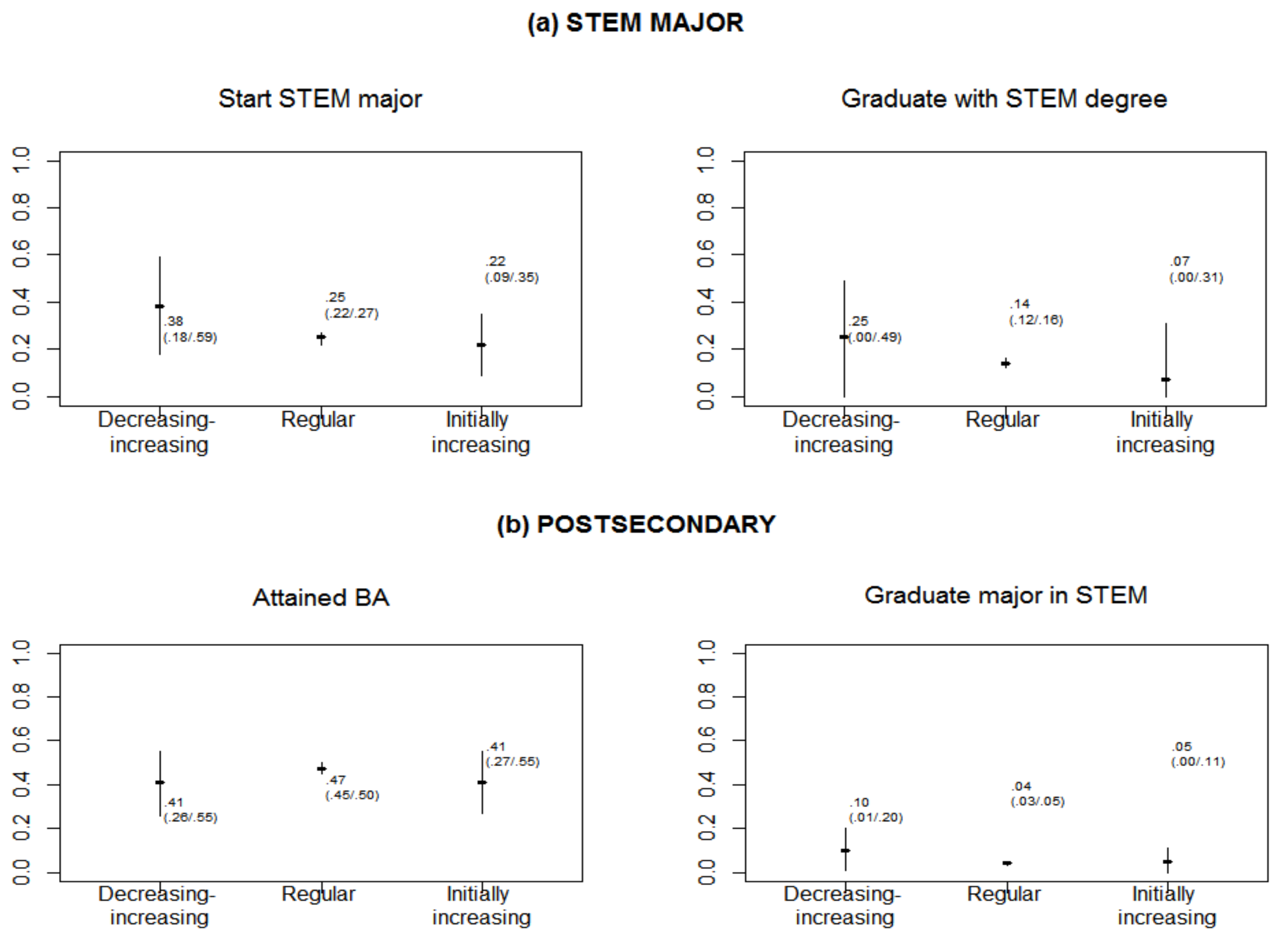

Figure 16. Predicted mean probability (and 95% confidence bands) of college outcomes associated with membership in latent classes of Science Utility.

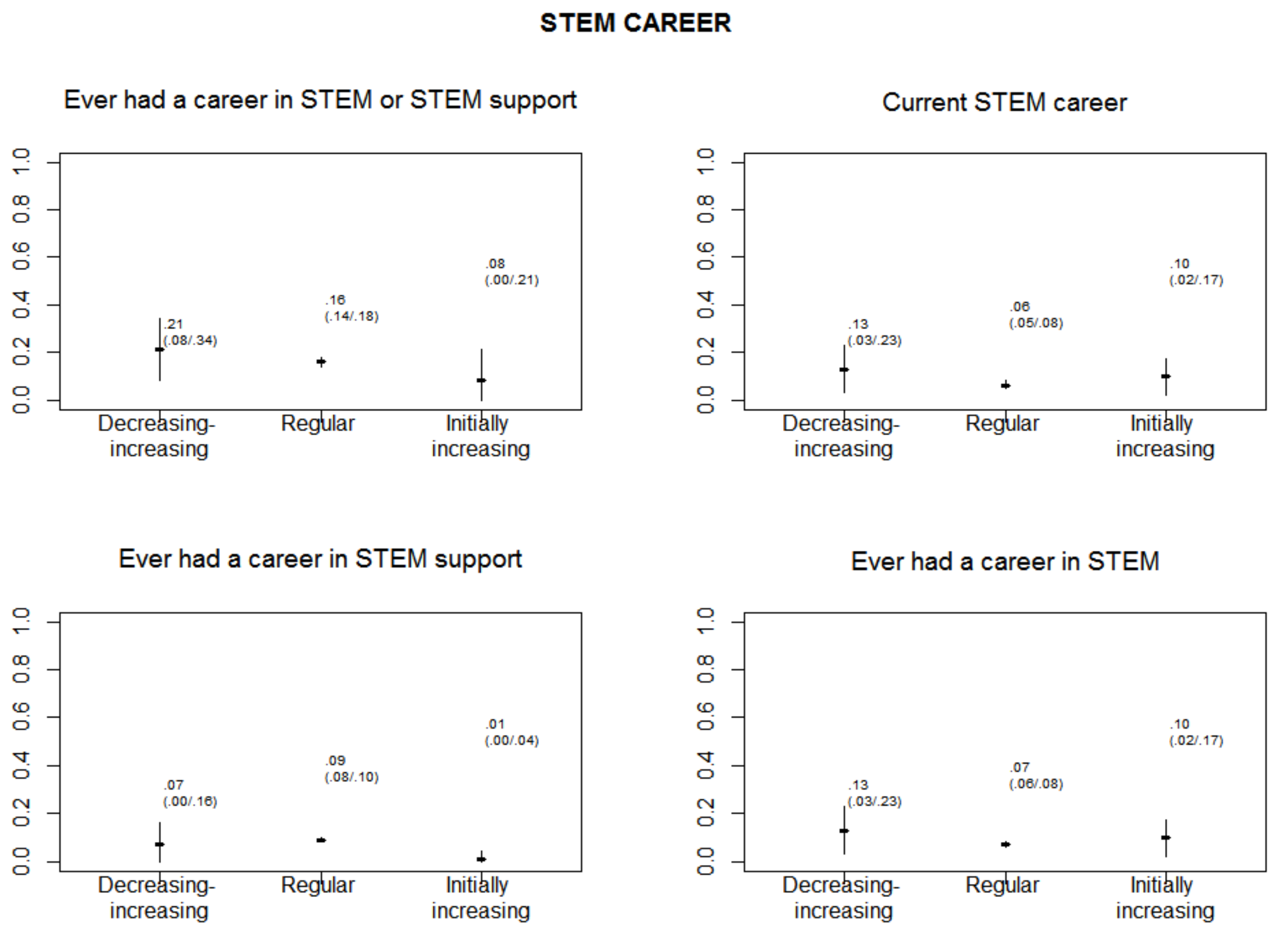

Figure 17. Predicted mean probability (and 95% confidence bands) of career outcomes associated with membership in latent classes of Science Utility.

Science self-concept. Figures 18.1 and 18.2 illustrate the relative probabilities of each distal achievement outcome associated with each latent growth class for Science Self-Concept. There is probabilistic separation of classes for almost all achievement outcomes, with membership in the Increasing class generally associated with more positive outcomes and membership in the Decreasing class associated with more undesirable outcomes. Members of the Increasing class were more likely to perform better on the Grade 12 standardized test, less likely to perform in worst quintile, and more likely to have a higher Grade 12 science course grade, take an advanced science course by Grade 12, and take an above average number of courses after biology. Of the achievement outcomes, only the results related to average science course grade were probabilistically indistinguishable by class.

Figure 19 illustrates the relative probabilities of each distal college outcome associated with each latent growth class for Science Self-Concept. Members of both the Increasing class and the Regular class were more likely to attain a BA than members of the Decreasing class. The Increasing Class also demonstrated a significantly higher chance of starting a major in STEM, finishing a major in STEM, and completing graduate work in STEM.

Figure 20 illustrates the relative probabilities of each distal career outcome associated with each latent growth class for Science Self-Concept. Individuals whose change trajectories were classified as Increasing were more likely to ever have had a STEM or STEM support occupation, and also more likely to have a current STEM career where current is defined as the last time the question was answered by an individual

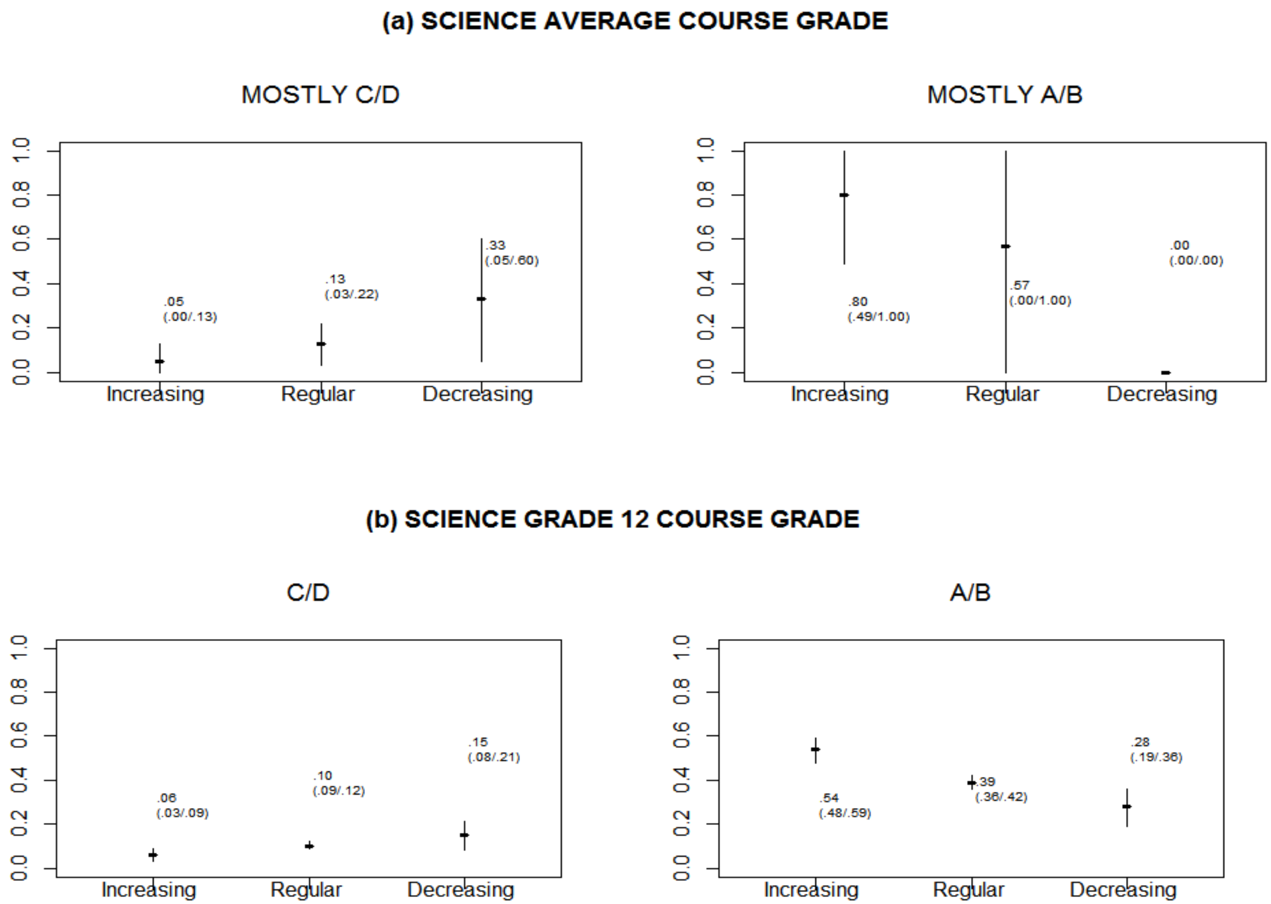

Figure 18.1. Predicted mean probability (and 95% confidence bands) of achievement outcomes (course grades) associated with membership in latent classes of Science Self-Concept.

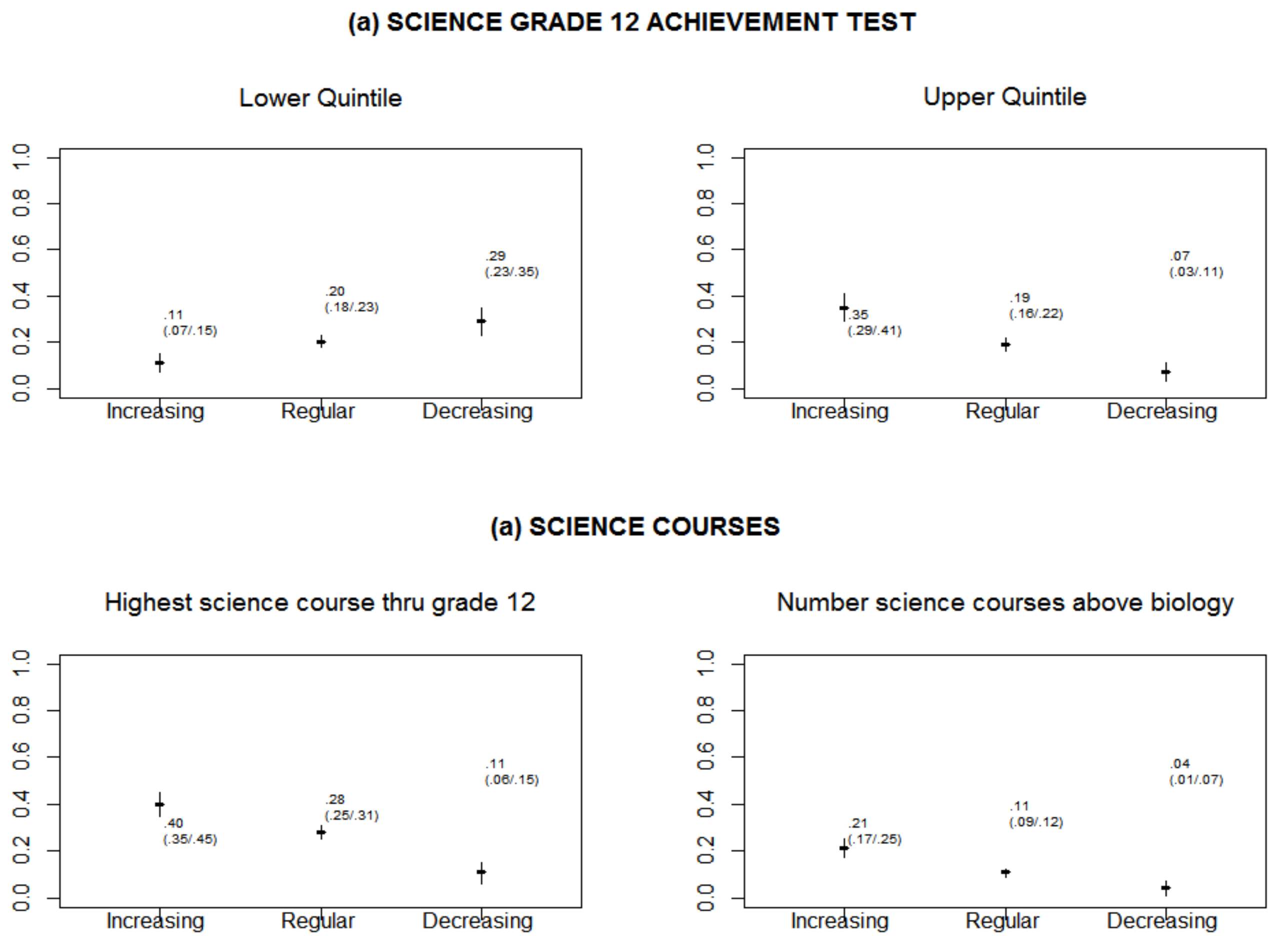

Figure 18.2. Predicted mean probability (and 95% confidence bands) of achievement outcomes (standardized science test and advanced science coursework) associated with membership in latent classes of Science Self-Concept.

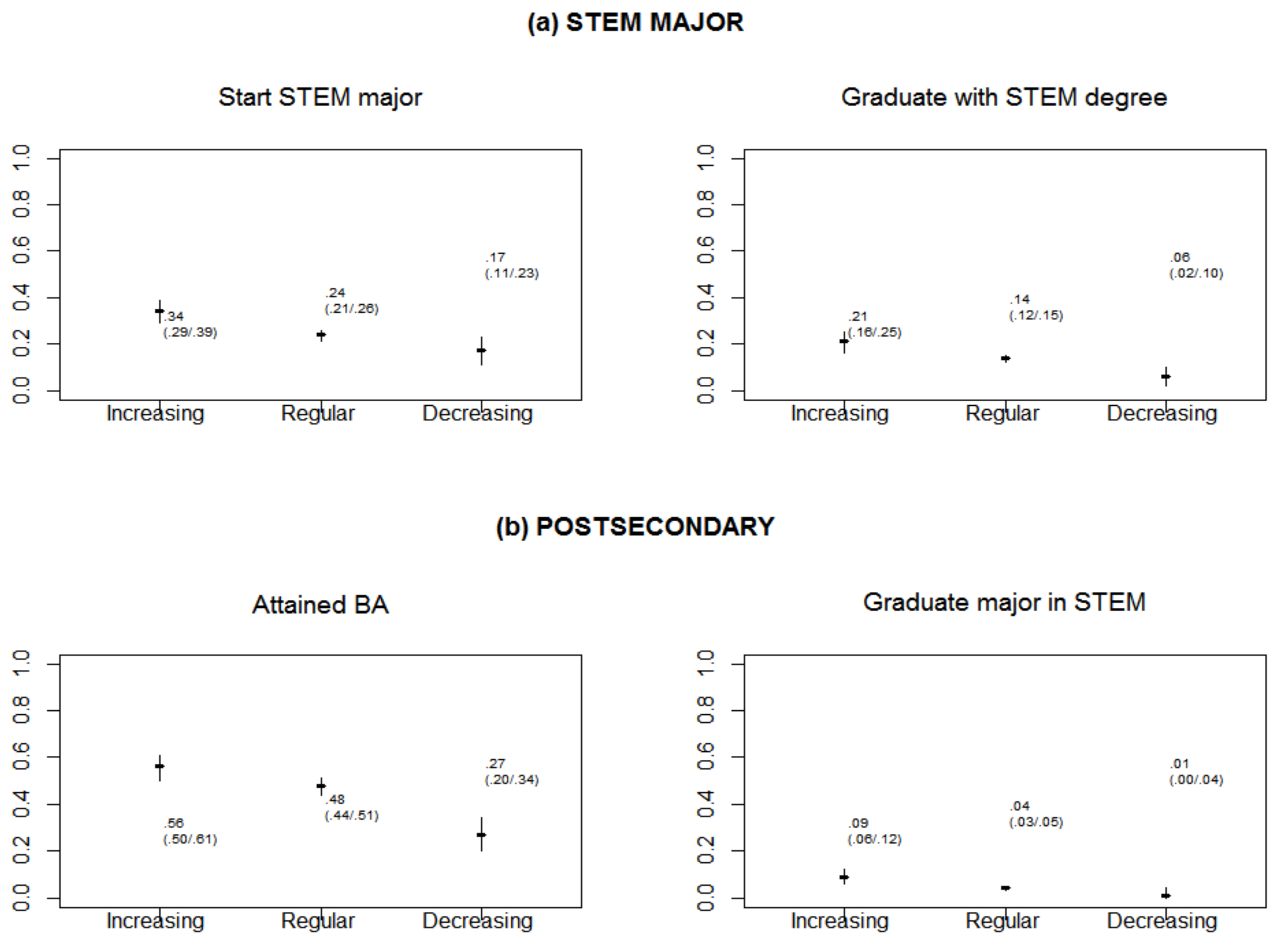

Figure 19. Predicted mean probability (and 95% confidence bands) of college outcomes associated with membership in latent classes of Science Self-Concept.

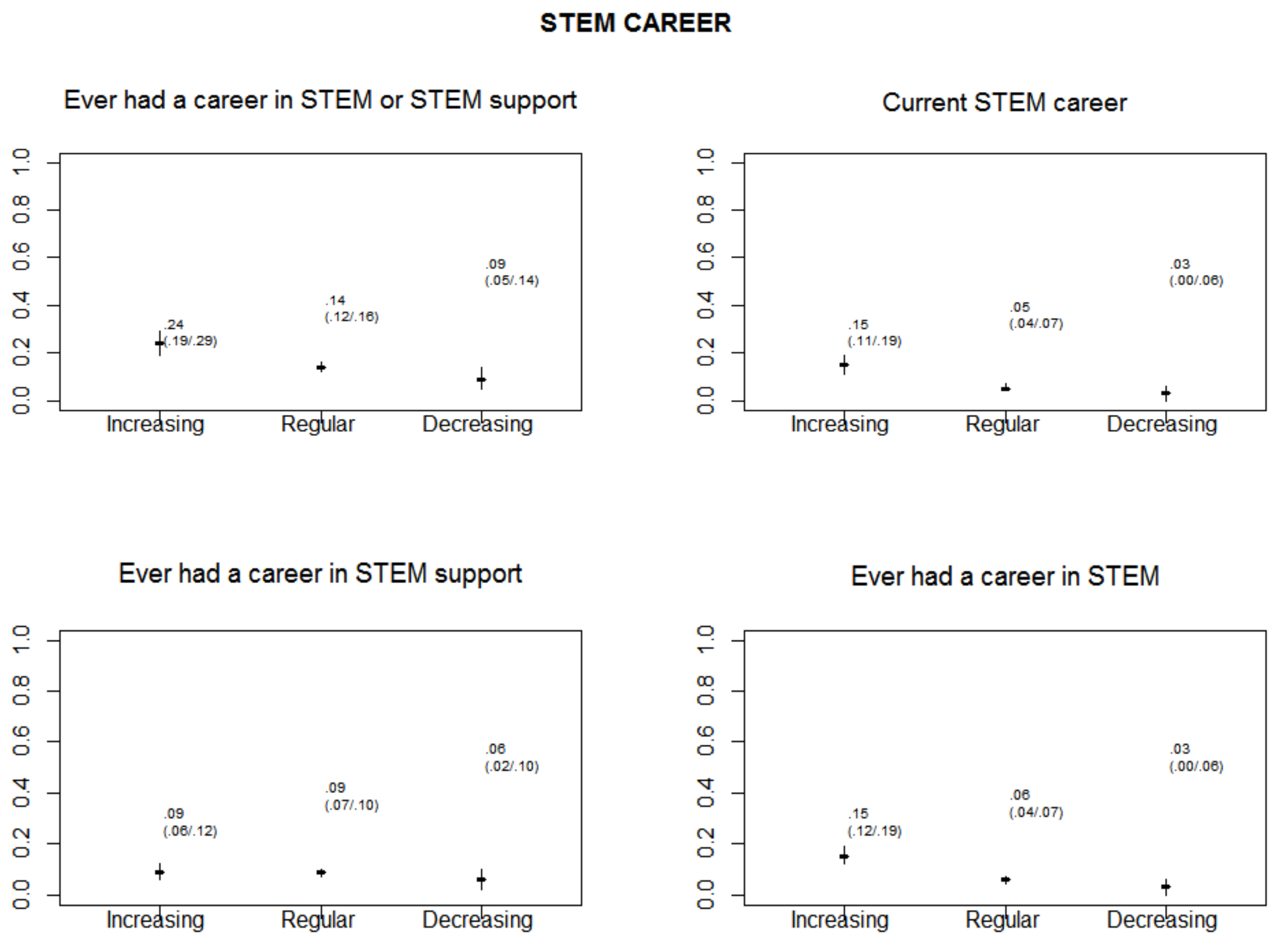

Figure 20. Predicted mean probability (and 95% confidence bands) of career outcomes associated with membership in latent classes of Science Self-Concept

during the follow up survey period (2007-2011). On these outcomes, the Average class and the Decreasing class were not significantly different from each other.

Multinomial Logistic Regression

Tables 13, 14, 15, and 16 report results of the generalized multinomial logistic regression of latent growth classes on possible explanatory variables. Only statistically significant main effects are included in these final models, with each explanatory variable appearing in a given table controlled for by all other variables appearing in that table. The Regular class was used as the reference group, as it was the largest for both attitudinal dimensions. This research proposed two sets of explanatory variables: one related to demographic and parental characteristics (set A), and one comprised of student, teacher, and parent initial expectations (set B). Correlations between all covariates were mostly low, with the highest between ‘parents expect college’ and ‘student expects 4-yr college’ at .40.

Science utility. For Science Utility change trajectories, the only significant association for the demographic and parent variables was whether the student is female. Student change trajectories were less likely to be classified as Decreasing if the student was female. This variable was not significant for the Increasing class.

There were three expectations variables that showed significant relationships with latent classes of change in attitudes toward utility of science. If a student reported expecting to have a STEM career (at age 40), they were less likely to have a change trajectory classified as Decreasing-Increasing. If the student reported that their teacher

Table 13. *Explanatory Relationship between Explanatory Variables and Latent Classes of Change in Attitudes toward Utility of Science (set A)*

Explanatory variable	Odds ratio (95% confidence limits)	% Risk increment[a]	%Risk reduction[b]
Odds for classification as Decreasing-Increasing (latent class 3) vs. Regular (latent class 1)			
Teacher encourages career in science	1.26 (0.55/2.89)		
Parents would like student STEM career	1.43 (0.60/3.40)		
Student expects STEM (when 40)	0.37 (0.15/0.94)		62.8
Odds for classification as Initially-Increasing (latent class 2) vs. Regular (latent class 1)			
Teacher encourages career in science	2.04 (1.19/3.48)	103.6	
Parents would like student STEM career	2.18 (1.33/3.56)	117.7	
Student expects STEM (when 40)	1.28 (0.79/2.09)		

Note. Values are estimated through multinomial logistic regression applying the generalized logit link function, where the latent growth classes are regressed simultaneously on explanatory variables and latent class 1 (Regular) is the reference group.

[a]Entries equal odds ratio - 1 (100).
[b]Entries equal 1 - odds ratio (100).

Table 14. *Explanatory Relationship between Explanatory Variables and Latent Classes of Change in Attitudes toward Utility of Science (set B)*

Explanatory variable	Odds ratio (95% confidence limits)	% Risk increment[a]	%Risk reduction[b]
Odds for classification as Decreasing-Increasing (latent class 3) vs. Regular (latent class 1)			
Student is female	0.62 (0.36/1.07)		
Odds for classification as Initially-Increasing (latent class 2) vs. Regular (latent class 1)			
Student is female	0.53 (0.34/0.82)		47.2

Note. Values are estimated through multinomial logistic regression applying the generalized logit link function, where the latent growth classes are regressed simultaneously on explanatory variables and latent class 1 (Regular) is the reference group.

[a]Entries equal odds ratio - 1 (100).
[b]Entries equal 1 - odds ratio (100).

Table 15. *Explanatory Relationship between Explanatory Variables and Latent Classes of Change in Science Self-Concept (set A)*

Explanatory variable	Odds ratio (95% confidence limits)	% Risk increment[a]	%Risk reduction[b]
Odds for classification as Increasing (latent class 2) vs. Regular (latent class 1)			
Teacher encourages career in science	1.61 (1.17/2.22)	61.3	
Parent expects do well in science	1.62 (1.22/2.14)	61.6	
Parents would like student STEM career	1.64 (1.25/2.16)	64.4	
Student expects 4y college	1.67 (1.23/2.29)	67.4	
Student expects STEM (when 40)	1.90 (1.46/2.47)	89.8	
Odds for classification as Decreasing (latent class 3) vs. Regular (latent class 1)			
Teacher encourages career in science	0.69 (0.36/1.32)		
Parent expects do well in science	0.68 (0.47/1.00)		31.7
Parents would like student STEM career	1.16 (0.67/1.99)		
Student expects 4y college	0.52 (0.36/0.75)		48.1
Student expects STEM (when 40)	0.58 (0.37/0.93)		41.7

Note. Values are estimated through multinomial logistic regression applying the generalized logit link function, where the latent growth classes are regressed simultaneously on explanatory variables and latent class 1 (Regular) is the reference group.

[a]Entries equal odds ratio - 1 (100).
[b]Entries equal 1 - odds ratio (100).

Table 16. *Explanatory Relationship between Explanatory Variables and Latent Classes of Change in Science Self-Concept (set B)*

Explanatory variable	Odds ratio (95% confidence limits)	% Risk increment[a]	%Risk reduction[b]
Odds for classification as Increasing (latent class 2) vs. Regular (latent class 1)			
Student is female	0.60 (0.48/0.75)		40.4
Parent has a BA or higher	1.52 (1.21/1.90)	51.9	
Odds for classification as Decreasing (latent class 3) vs. Regular (latent class 1)			
Student is female	0.97 (0.71/1.33)		
Parent has a BA or higher	0.61 (0.42/0.90)		38.6

Note. Values are estimated through multinomial logistic regression applying the generalized logit link function, where the latent growth classes are regressed simultaneously on explanatory variables and latent class 1 (Regular) is the reference group.

[a]Entries equal odds ratio - 1 (100).
[b]Entries equal 1 - odds ratio (100).

encouraged a career in science or that their parents would like them to have a career in STEM, they were more likely to be in the Increasing class. Inasmuch as these variables were measured in timepoint 1 (Grade 7), they seem to comport reasonably with the estimated trajectories and distal outcomes associations.

Science self-concept. The demographic and parent variables yielded two significant explanatory variables for classes of Science Self-Concept change trajectories: whether the student is female and whether one or more parent has a BA. Membership in the Increasing class was more likely if parent had a BA, and less likely if the student was female. Conversely, membership in the Decreasing class was less likely for students who had at least one parent with a BA.

Parent, teacher, and student initial expectations seemed to have strong associations with odds of classification for both the Increasing class and the Decreasing class. Student change trajectories were more likely to be classified as Increasing if their teacher encouraged a career in science, their parent expected them to do well in science, their parent expected them to have a STEM career, and the student expected to go to a four year college or to have a STEM occupation (when age 40). In contrast, students were less likely to have trajectories classified as Decreasing if their parents expected them to do well in science, the student expected to go to a four year college, or the student expected to have a STEM occupation (when age 40).

CHAPTER 4: DISCUSSION

Overview

Methods. The methodological objective of this research was to apply latent growth mixture modeling to aspects of student attitudes toward science and core self-concept. The nature of the data used presented several challenges, including a complex missing data problem, constructs of interest that were represented by multiple items from nonestablished scales, and complicated nesting within classrooms, teachers, schools, and across time. Although efforts were taken to account for much of this, any of these concerns may have contributed to the failure of some constructs to produce reliable or valid subgroups of change patterns. As an essentially data-driven exploratory method, latent growth mixture modeling is very sensitive to idiosyncrasies in the data and may have been affected by imputation and scaling strategies. Yet, problems of this nature are not uncommon when dealing with large longitudinal public data sets, and it is beneficial to explore approaches to mitigate them while still conducting an informative analysis.

Results. Three distinct patterns of developmental trajectories were found each for Mastery Motivation (an aspect of core self-concept), and the two attitudinal dimensions of Science Utility and Science Self-Concept. Although the Increasing-Decreasing class of Mastery Motivation appeared to be associated with more negative outcomes, no conclusions could be drawn in terms of characterizing its members. Differential membership in the Science Utility classes seemed to have no bearing on outcomes, suggesting that if the trajectory does indeed matter it may be in conjunction with other factors. Science Self-Concept subgroups were fair predictors where the Decreasing class was associated with negative college and career outcomes and the Increasing class with positive outcomes. For both classes of attitudinal dimensions, gender was associated with classification in a way that supports prior research in this area. In general, higher initial student, teacher, and parent expectations signaled classification into subgroups with more positive outcomes.

Review of Findings

Over the past several decades, social and behavioral researchers have proposed a variety of theories attempting to explain or in some way integrate the relationships between beliefs, personality, self-perceptions, and individual differences in school performance, learning, and other measures of achievement (e.g. expectancy-value theory, goal orientation theory, attribution theory, social-cognitive theory, self-determination theory) (Cook & Artino, 2016). This research centered on two common aspects of these theories: self-concept, or an individual's own assessment of their general competence, confidence, and ability to perform well; and task value, or attainment value, dominated by perceived domain utility and intrinsic motivation. Partially due to the way the relevant items were administered in the original questionnaires, facets of self-concept and task value were mixed together, with one set of items more related to those usually associated with self-evaluations and one set focused on attitudes toward science. A dimensional analysis was thus required to clarify the constructs before moving forward.

The purpose of applying growth mixture modeling to student self-evaluations and attitudinal data was to explore the possibility of intragroup variation over time within multiple hypothesized subgroups, where the groups were not defined a priori but rather identified by an unobserved grouping variable. This would enable detection of differences in how change proceeds over subsamples of the population. Using an iterative estimation process, latent growth mixture models reveal underlying normal distributions, where the distributions of intercepts and slopes within classes are assumed to be multivariate normal but the distribution over classes is not, and probabilistically identify the members of each class. It was posited that these classes, or subgroups of trajectories, might be linked to science achievement, college, and career outcomes, or associated with demographic and parent variables or high student, teacher, and parent future expectations. The following section reviews and discusses the findings by research question.

Core Self-Evaluations

RQ1: Are there latent and longitudinal subgroups (developmental trajectories) of student positive self-concept as they progress through middle and high school?

Three reliable constructs were found for core self-evaluations measures: Self-Esteem, Locus of Control, and Mastery Motivation. Of these, subpopulations of trajectories failed to emerge for Self-Esteem and Locus of Control. This finding indicates that there are no latent subpopulations of trajectories for student feelings of self-worth or fate control discernable over middle and high school. This finding is contrary to prior research utilizing cluster analysis of growth curves, which had been able to identify four groups of trajectories of self-esteem for adolescents in Grades 6-10 (consistently high, moderate and rising, steadily decreasing, consistently low) (Zimmerman, Copeland, Shope, & Dielman, 1997; Hirsch & DuBois, 1991), and the four latent classes of trajectories identified through growth mixture modeling among students Grades 7-10 in

Montreal by Morin, Maiano, Marsh, Nagengast and Janosz (2013). This disparity could be due to a number of factors, including differing sample characteristics, age range, instrumentation, and methodology. In particular, the measure of self-esteem in the current research contains only four of the ten items from the Rosenberg Self-Esteem scale, which had already been modified by the original study researchers to include only six of the items with an additional anchor point. Since the reliability of measures may be compromised as items are removed from the original item set (Kingston & Tiemann, 2010), for the purpose of this research the six self-esteem items were analyzed together with the other items in that item set rather than being extracted as their own common scale. This resulted in a shortened four-item instrument to measure self-esteem, with the other two self-esteem items loading on the Locus of Control scale. It is possible that latent subpopulations might indeed exist, but given the shortened instrument and more heterogenous population the method was not sensitive enough to detect enough parameter separation to identify them.

Three latent classes of developmental trajectories were found for Mastery Motivation. As there is some literature indicating that intrinsic motivation becomes more stable over time, and notably during adolescence (Gottfried et al, 2001), the finding of an extremely dominant stable class of trajectories for Mastery Motivation is not unsupported. However, this model also produced some insignificant slope components for the other two classes, making the certainty around the shapes of the trajectories questionable. Although subsequent analyses proceeded with the model, the aim was to examine whether the classifications bore any relationship to outcomes and covariates, rather than relating their shapes to those relationships.

RQ3A & RQ4A: Do these subgroups signal student science achievement at the end of high school? Do these subgroups signal student college and career outcomes?

The Increasing-Decreasing class appeared to be associated with negative science achievement, college, and career outcomes. This seems to comport with the idea that lower levels of Mastery Motivation would result in lower probabilities of achieving or majoring in STEM, as higher intrinsic motivation is often related to higher academic achievement. Interestingly, while members of this class were less likely to be in high performing achievement categories, they were not more likely to be in low performing categories. However, their mean probability of a current STEM career was near zero, a finding in line with the findings of near zero mean probability of having a graduate major in STEM, .05 probability of graduating with a STEM degree compared to .15 for the Regular class, and .32 probability of gaining a BA compared to .49 for the Regular class.

The Decreasing-Increasing class was indistinguishable from the Regular class in terms of distal outcomes. The Decreasing-Increasing class did produce a point estimate for starting a STEM major somewhat higher than that for either class—this would make sense theoretically as students with higher levels of curiosity and mastery motivation are traditionally thought to be more apt to engage in scientific pursuits. This association was also statistically insignificant, however, as were many of the results of the binary distal student outcomes regressed on the resultant latent subgroups.

Although the class sizes based on estimated posterior probabilities had been deemed sufficient for the 3-class model for Mastery Motivation, there is some concern about inadequate power in the distal outcomes and explanatory covariates analyses. Class sizes may have been too small to adequately detect effects, especially as the classification based on most likely class membership—which was used for subsequent analyses after model selection—yielded classes somewhat smaller than initially anticipated. Usually the three estimates of class size (based on the estimated model, estimated posterior probabilities, and most likely latent class membership) should be similar. However in this case, the most likely membership, where class assignments are made ensuring that individuals are not split across classes, was significantly lower than the other two estimates. Results should thus be interpreted with caution as this indicates lower confidence in class membership. While there is some research suggesting that mastery approach orientation and cognitive performance are not highly correlated, and that mastery approach is a poor predictor of achievement (Seaton et al, 2014), this is an area worthy of further investigation, especially since the Increasing-Decreasing class did demonstrate some degree of reasonable separation from the Regular class and the error bands around even the significant findings were quite large for the two smaller classes, indicating a substantial amount of uncertainty.

RQ5A & RQ6A: To what extent are initial parent and demographic factors associated with memberships in these subgroups? To what extent are initial student, parent, and teacher expectations associated with memberships in these subgroups?

None of the hypothesized covariates were significantly related to any of the classes, making them difficult to characterize. This may also be due to small sample size, but, taken together with the indeterminate result of the distal outcomes analyses, which failed to distinguish the Decreasing-Increasing class, indicates a lack of conclusive evidence on which to base these classifications. As this was an exploratory analysis driven in large part by the data, it may be that there are other unknown, untested covariates associated with the separation of the classes. Care should be taken in attempting to use these findings to further understand the relationship between temporal change in student motivation and science achievement, college, and career outcomes.

Attitudes toward Science

RQ2: Are there latent and longitudinal subgroups (developmental trajectories) of student attitudes toward science as they progress through middle and high school?

Two reliable constructs were found for attitudinal measures: Utility of Science and Science Self-Concept. The Utility of Science measure was mainly driven by student feelings on present and future usefulness of the domain while Science Self-Concept reflected a combination of anxiety toward the subject and confidence in own science ability. There was some overlap in that items indicating enjoyment and self-perceived ability in the subject loaded on both constructs, but the correlation between constructs was only moderate. Three subpopulations of trajectories were uncovered for each measure, indicating that distinct subgroups of trajectories for student attitudes toward science exist through middle and high school.

Each attitudinal dimension resulted in one dominant class of fairly flat trajectory, as well as two other more dynamically shaped classes. Though in general researchers find a steady decline in student attitudes toward science in secondary school (Barmby, Kind, & Jones, 2008), this was not the case here. This could be due to different measurement tools, different populations, or that the current study might in fact be measuring a slightly different attitudinal construct. The constructs being examined in this research are only two facets of science attitudes: utility and domain-specific self-concept. The distinction is important; for instance, other studies have found that while attitudes toward school science decline, attitudes toward the usefulness of science remain stable (Schibeci, 1984; Osborne et al., 2003)

As data was collected each year on course-specific attitudes, the scores for Utility of Science and Science Self-Concept at timepoint 1 (Grade 7) were correlated with the corresponding questions on utility and enjoyment of the student's current science class to establish some validity. However, unlike the typical high school mathematics or English curriculum, the courses in a typical high school science curriculum do not necessarily build off of each other or cover similar content areas. For instance, many high school students will take both biology and physics, but though both subjects are categorized as 'science' they are vastly different fields, require different skill sets for success, and will lead to different sorts of careers. It is entirely possible that a student may exhibit great skill or interest in one scientific discipline while performing poorly in another. Even as the attitudes scales in this study were not linked to specific courses, a student's course history may well have an impact on the shape of their trajectory. Regarding the LSAY

Cohort 2 data, the majority of students were enrolled in life science (69%) in Grade 7 (*N* = 2,788) and earth or physical science (73%) in Grade 8 (*N* = 2,621). The variation increased dramatically in Grade 9 (*N* = 2,397) with 33% physical science, 32% biology, 17% earth science, 9% general science, 9% other; Grade 10 (*N* = 2,323) with 56% biology, 15% chemistry, 8% physical science, 21% other; Grade 11 (*N* = 1,787) with 49% chemistry, 13% physics, 12% biology, 10% advanced biology, 15% other; and Grade 12 (*N* = 1,122) with 39% physics, 22% advanced biology, 14% chemistry, 9% advanced physics or chemistry, 16% other. Given this heterogeneity, it is conceivable that some of the individual variation in attitudes toward utility or self-concept is attributable to the differing natures of these courses and individual variation in course tracking.

This is an area suitable for future investigation, as the directionality of the relationship between curriculum and attitudes may also be reciprocal or reversed. It is outside the scope of the current research, but subsequent work may find it useful to build off of the subgroups of developmental trajectories uncovered here. For the present purpose, three reliable longitudinal subgroups for each attitudinal dimension were found using unconditional models, driven by the data but no covariates.

RQ3B & RQ4B: Do these subgroups predict student science achievement at the end of high school? Do these subgroups predict student college and career outcomes?

Science Utility attitudes do not seem to be particularly good predictors of either science achievement or science college and career outcomes. For achievement, there are some nonsignificant estimates pointing toward members of the Decreasing-Increasing class being more likely to take more courses than average above biology and members of the Initially-Increasing class being less so; they are also non-significantly less likely to have Cs and Ds in Grade 12 science, though only 60% of the dataset has a course grade for Grade 12 science, meaning that some students did not take a Grade 12 science class. Dropping science would be expected from students who either lack interest in science or are not performing particularly well in it, and most high schools do not require four years of science for a high school diploma. On average for science course grades, the Regular class is significantly more likely than the other two classes to have achieved mostly As and Bs, at .70 to .28 for Decreasing-Increasing and .06 for Initially-Increasing, and members of the Initially Increasing class are more likely to have Cs and Ds than the Regular class, which has a probability near zero.

By point estimate the Decreasing-Increasing class has a higher probability of STEM career outcomes than the Regular class, while the Initially-Increasing class has a lesser one. This is irrespective of whether the career is in STEM support or STEM professional, but is reasonable within the context of expectancy-value, where an increase in attitudes toward science utility that is more proximal to the expected goal of a STEM career should be able to predict it better. This is also true of starting and finishing a STEM major and graduating with a STEM degree; however, none of it is statistically significant, indicating uncertainty of actual probabilistic separation between classes for these outcomes.

The inability of Science Utility class membership to predict distal outcomes of achievement or career is not terribly surprising. First, utility is an aspect of interest, and prior work has shown inconclusive correlations between interest and achievement (Krapp & Prenzel, 2011). Demonstrating interest alone is not enough to ensure success, since, as discussed previously, interest and achievement both are thought to be essential in encouraging persistence. There are a myriad of explanations for why an individual's perception of the utility of science might change, including an interest in a scientific field they were previously unexposed to, the prospect of a high-paying or dynamic career, teacher or peer encouragement, or influences by entertainment or media. But an increase in interest is not necessarily matched by an increase in ability, and certainly not at the same rate.

While interest has an uncertain association with achievement, domain-specific anxiety does have a moderate correlation with academic achievement (Stankov et al, 2014), and Marsh and Martin (2011) actually posit a reciprocal model of interrelated achievement and academic self-concept. The results of this study seem to support an association, with the Increasing class of Science Self-Concept related to positive achievement outcomes and the Decreasing class related to negative achievement outcomes. Distinct separation of classes is clear with the Increasing class both more likely to be in the upper science achievement test quintile and less likely to be in the lower quintile, as expected, and higher probabilities of advanced science coursework, which comports with the findings of Pajares (2005). Interestingly, no real separation in course grades on average where there are large error bands, but the Grade 12 courses follow the pattern of the other science achievement measures with the Increasing class more likely to achieve A/Bs and less likely to have C/Ds. This is logical considering that academic self-concept tends to be at least partially informed by feedback on ability, such as course grades, and averaging across course grades may hide or distort changes in grades. Future work might consider tracing trajectories of course grades as well as trajectories of other achievement variables and comparing them to the longitudinal subgroups determined by this analysis.

Science self-concept subgroups were also fair predictors of college and career outcomes. The Decreasing class was associated with negative college and career outcomes, where its members were less likely to obtain a BA in any field than those of the Increasing or Regular classes (.27 compared to .56 for the Increasing class) or graduate with a STEM degree. The Increasing class was significantly more likely than both other classes to start a STEM major, graduate with a STEM degree, and have a graduate major in STEM. Though the probabilistic separation of classes was nonsignificant for STEM support careers, it was significant for STEM professional careers, at .15 for the Increasing class, .06 for the Regular class, and .03 for the Decreasing class. Insofar as self-perception of ability is concerned, then, those with increasing confidence in their abilities in science had higher probabilities of desirable science achievement outcomes and were more likely to pursue it as a career, where those with decreasing confidence had higher probabilities of undesirable science achievement, college, and career outcomes.

RQ5B & RQ6B: To what extent do initial parent and demographic factors determine memberships in these subgroups? To what extent do initial student, parent, and teacher expectations determine memberships in these subgroups?

Age and gender differences in attitudes toward STEM have been well supported in the literature (Barmby, Kind, & Jones, 2008; Christidou, 2011; Wang, Degol, & Ye, 2015). Wang, Degol, and Ye (2015) found that math achievement in Grade 12 was a mediator for gender and STEM career attainment, but that math task value also partly explained gender differences in STEM career outcomes. Christidou (2011) found evidence of gender differences by science subject area, in that females generally liked biology better, neither gender preferred chemistry, and males opted more for scientific professions. Researchers (Barmby, Kind, & Jones, 2008; Correll, 2001) have also observed that males are usually more positive in their self-ratings of ability and have a less negative attitudinal development trend. On the whole much of this is supported in the current study. For both the Science Utility classes and the Science Self-Concept classes, categorization into the Initially Increasing and Increasing class, respectively, was less likely for females.

Parent, teacher, and student initial expectations also operated as strong explanatory factors. Students were more likely to be classified into the Initially Increasing Science Utility class likely if their Grade 7 teacher encouraged a career in science and parents wanted them to have STEM career. They were less likely to be classified into the Decreasing-Increasing class if they wanted to have a career in STEM, as reported in Grade 7. That is quite reasonable since the student expectation of a STEM career was an initial estimate and it is possible that at some point as students progress through school they start considering STEM investment as a more or less worthy endeavor. Students were more likely to be classified into the Increasing class if at least one parent had a BA, and if teacher, parent, and students initial expectations were all high. They were less likely to belong to the Decreasing class if their parents expected them to do well in science, at least one parent had a BA, and the student had high initial expectations. This corresponds with the idea that home and family factors such as parent education and encouragement of science enhance the likelihood of entrance into STEM (Miller & Kimmel, 2012), where the class with the greater relative probability of entrance into STEM was also the one associated with students whose parents were more likely to have college degrees and support future student efforts in science.

Summary

A variety of variables representing science achievement, college, and career outcomes were chosen for this study. Cognizant of the fact that many of the outcomes selected are dependent on each other (e.g. an individual is much more likely to attain a graduate degree in STEM if they first have an undergraduate degree in STEM), the outcome of 'STEM support career' and the potential covariate 'student expects 2-year college' were also examined. This with the assumption that a 2-year college generally has a lower achievement bar, if low science or math achievement was a barrier to entry to a 4-year STEM degree, and the expectation that STEM support occupations do not require 4-year degrees. Notably, student expectation of entering a 2-year college was not a risk or protective factor for any class in any dimension, although expectation of entering a 4-year college was. Additionally, there was very little difference in class membership's ability to predict a STEM career versus a STEM support career, except in the case of the Science Self-Concept classes. Membership in the Mastery Motivation Increasing-Decreasing class or the Science Self-Concept Decreasing class was generally associated with negative STEM career outcomes, whereas membership in the Science Self-Concept Increasing class was associated with positive STEM career outcomes.

Starting a STEM major is usually driven by interest or expectancy value, where completing it requires persistence—thus those were also analyzed separately. Tables 17 and 18 illustrate the sample frequencies of selected distal postsecondary and career outcomes. Approximately 67% of the sample reported on the outcomes of interest, with only a small percentage of them actually going on to major in STEM or pursue a STEM-related career. Membership in the Mastery Motivation Increasing-Decreasing class or the Science Self-Concept Decreasing class was generally associated with negative postsecondary outcomes, whereas membership in the Science Self-Concept Increasing class was associated with positive postsecondary outcomes.

Table 17. *Sample Postsecondary Outcome Frequencies*

Distal Postsecondary Outcome	*n*	Percent
STEM Graduate Major[a]	97	4.6
Started STEM Major (College)[b]	517	24.8
Completed STEM Major (College)[c]	288	13.8
Attained BA[a]	968	46.2

[a]$N = 2097$.
[b]$N = 2084$.
[c]$N = 2086$.

Table 18. *Sample Career Outcome Frequencies*

Year	Out of Workforce	Non-STEM	STEM Support	STEM Professional
2007 ($N = 2097$)				
n	339	1464	149	145
%	16.2	69.8	7.1	6.9
2008 ($N = 1344$)				
n	216	927	94	107
%	16.1	69.0	7.0	8.0
2009 ($N = 1334$)				
n	227	912	93	102
%	17.0	68.4	7.0	7.7
2010 ($N = 1674$)				
n	269	1164	114	127
%	16.1	69.7	6.8	7.6
2011 ($N = 1644$)				
n	252	1146	125	121
%	15.3	69.7	7.6	7.4
Current ($N = 2098$) [a]				
n	335	1469	150	144
%	16.0	70.0	7.2	6.9

[a] Represents respondent's most recent response to this question

Since it is well discussed in the literature that standardized test scores are not always the best predictors of college performance, other measures of achievement were included such as number of science courses above biology, advanced science course-taking, average and Grade 12 course grades. On average the directionality of these associations with the various subgroups of development trajectories appeared to agree with each other. Membership in the Mastery Motivation Increasing-Decreasing class or the Science Self-Concept Decreasing class was generally associated with negative achievement outcomes, whereas membership in the Science Self-Concept Increasing class was associated with positive achievement outcomes.

Growth mixture modeling yields information on how many subgroups there may be, how they differ, and who is a member of which, but does not yield enough information to determine causality. This analysis found that Mastery Motivation subgroups did not exhibit strong or certain enough associations with theoretically relevant explanatory covariates or distal outcomes to enable any concrete conclusions about the role motivation might play in influencing STEM persistence or outcomes. Science Utility and Science Self-Concept subgroups of developmental trajectories both demonstrate plausible and appropriate associations with relevant explanatory covariates. Though the Science Utility subgroups did not show significant impact on relevant distal outcomes, upon reflection this is not necessarily surprising and may be grounds for future, more in-depth investigation. Science Self-Concept subgroups did demonstrate significant and reasonably distinct associations with relevant science achievement, postsecondary, and career outcomes.

Limitations and Future Directions

Multilevel Data

The data in this study was drawn from a probability sample of schools stratified by geographic region and urban development. Thus it was by design multilevel, with students nested within classrooms nested within schools nested within the combined region/urban development sample stratum. Although most of these groupings were recorded in the dataset, the nature of the research questions investigated here would have necessitated an extremely complex hierarchical structure for which results may have proven difficult to interpret. As this research was interested in Grades 7 to 12, most students passed through at least two schools: a middle school or junior high school and a high school or senior high school. Additionally, although in Grades 7 and 8 many students take only one science course, this number increases in upper grades, with 39 students reporting a second science course in Grade 10, 79 in Grade 11, and 86 in Grade 12. As the questionnaire only asked about the first two, there is no way to know the details of any additional science electives. As well, many schools are in the habit of assigning multiple types of course to one instructor or many sections of one course to one instructor, confusing the classroom v. teacher effects, and this may vary from year to year.

Throughout the time encompassed by this study, then, a typical student may have passed through two schools, four or five science courses, and multiple teachers. Traditionally, including multilevel effects would allow for determining or controlling for effects related to school context, classroom environment, teacher personality and classroom practice and instruction. Indeed there has been some research suggesting mediating and moderating effects of school context on attitudes and achievement (Wang & Eccles, 2013) and the effects of classroom experiences on change trajectories of self-concept and task value for mathematics (Eccles, Midgley et al, 1993).

Unfortunately, estimating these effects was simply infeasible in the current study, especially as it would involve some degree of summarizing over multiple teachers, classrooms, and schools. While the full Cohort 2 sample had started with 52 schools in Grade 7, this had ballooned into 277 schools by Fall of Grade 8 with the Fall Grade 12 school codes variable showing 520 schools, indicating even further dispersion of students to schools outside the original sample. In Grade 7 students were instructed by 140 teachers (*M* = 19 per teacher) in 393 classes (*M* = 7 per class), while at Grade 12 they were enrolled in 579 classes (*M* = 2 per class) taught by 278 teachers (*M* = 4 per teacher). Moreover, even at Grade 7, not every student was enrolled in the same science subject, making it difficult to separate subject-specific effects from school, class, or teacher effects. This difficulty only multiplies as students progress into higher grade levels.

For the particular aims of the current study, the nesting was considered mostly irrelevant. The goal was to determine whether subgroups of trajectories existed, and then to explore what their distinguishing characteristics or predictive abilities might be based on prior literature and theory. This study drew its variables exclusively from the student self-report questionnaires and standardized test data, so was not influenced by biases implicit in observer ratings such as those by teachers, parents, or school administers which would have made accounting for the nesting more essential. Given this, the dimensional analysis instead focused on establishing invariance of measurement across timepoints, with the scoring based on the parameters from Grade 7 so that change could be detected. Potential design effects could not be integrated into the growth models in any case, as there is currently no practical mechanism for estimating longitudinally nested parameters in latent growth mixture modeling.

Data on school context, classroom environment, teacher characteristics, and instructional practice were actually collected as well from teachers and school administrators, and could be used in future work to explore their relationships with trajectories of student attitudes toward science and self-concept. Although it was considered unworkable to attempt to account for them within the scope of the current study, it might be illuminating to classify or profile them in some way and then trace trajectories of certain types of classroom or teacher experience.

Future directions could include analyzing the trajectories uncovered in the current study together with trajectories of peer, teacher, or parent push or achievement (see Arcgambault, Eccles, & Vida, 2010 for an example using multiple process mixture modeling with literacy). It might also be illustrative to explore the interactions between trajectories and individual student science curricula, attitudes toward mathematics, and course-specific attitudinal variables. Attitudes toward science increase in Grades 11 and 12, possibly because those students actually taking courses in those grades are taking advanced, noncompulsory courses (Summer, 2016). Another investigation might center on attempting to disentangle the effects due to mathematics attitudes and effects due to science attitudes—these are linked more in some scientific disciplines than others, and are often simply analyzed together. In the case of this study, only attitudes toward science were examined, but the outcomes variables included STEM as a general category rather than domain-specific. The reasoning behind this is described further in the Censes Occupational Codes section.

Missing Data

Missing data were a major consideration in this study as, like in many longitudinal studies, there was a significant amount of attrition plus intermittent dropout. This study also covered two different waves of data collection: one from 1987-1994 and one from 2007-2011. As the second wave contained outcomes of interest rather than dependent variables of interest, no effort was made to impute and all analyses using those variables were based on listwise deletion.

To allow for factor analysis and scaling, missing data were imputed first at the item level. Although the best predictor of a variable at a missing timepoint is often the same variable at the timepoints prior and after, a decision was made to impute at each timepoint separately. First because the ultimate intent of the study was to examine change over time, and second to avoid imputing entirely missing cases at the item level. Missing data were treated again within the latent growth mixture models, where scores for missing timepoints were imputed for all nonmissing cases. Ancillary analyses were performed with those individuals with scores at all timepoints to check that the estimation of model parameters was not unduly influenced by the imputation.

Self-report and Validity of Items

As the constructs of interest were not measured by common scales, other than the modified Rosenberg Self-Esteem scale, findings from this study may not be immediately generalizable without more work around establishing the validity of the scales. Self-report of attitudes: each student is working from their own unknown baseline of agreement and disagreement.

An additional area of note is that, while all items comprising the dependent variables were ordinal items derived from Likert scales, the middle anchor point was labeled ‘Not Sure’ rather than ‘Neutral’ or ‘Neither Agree nor Disagree’. This makes sense in the context of some items but not others, and is not really a valid ordered anchor, potentially leading to confusing or misleading distributions. However preliminary analyses of skew, kurtosis, and response patterns indicated that students were treating this anchor as a middle ground between ‘Agree’ and ‘Disagree’, with no major dips or peaks that would suggest treating the category as missing data.

The Recession of 2007-2009

As with all longitudinal studies, the data cannot be removed from the context in which it was collected, which means it must be fit into the larger economic and social picture of that time. Generalizability of these findings will be somewhat limited. First, because though the LSAY was designed as a stratified random sample, this analysis was unable to account for that in a way that would allow retention of the full benefits of that process. Instead the current sample prioritized maintaining a large enough sample with which to conduct analyses, handling the complex missing data problems, and accommodating the technical demands of the analyses.

Second, the recession of 2007-2009 resulted in a national unemployment rate ranging from 5% at the end of 2007 to 10% in October 2009, with a notably high proportion of long-term unemployed (BLS, 2012). During times of economic downturn, generally young people tend to invest more in postsecondary education in the hopes of gaining skills while waiting for a better job market. The LSAY Cohort 2 population, having been in Grade 7 in 1987, would have been in their early thirties in 2007. The majority of them were probably midcareer by then, though some may have been finishing or even starting graduate school or a delayed undergraduate or community college degree. The industries hit hardest by the 2007-2009 recession were construction and manufacturing, with financial activities notable in that it experienced a 3.9% decline where it was usually unaffected by recessions. The 2007-2009 recession was also remarkable for its number of mass layoffs. On the other hand, employment in education and health services continued to increase during the recession, as it had for much of the previous years. The extent to which this affects the current study is unknown without more investigation into the mechanisms of the recession and delving into the exact nature of the occupational coding on the 2007-2011 questionnaires, which was outside the scope of this research.

The Census Occupational Codes of 1970

Although there were separate items in the questionnaires concerning mathematics and science, they were treated as one large 'STEM' domain in the outcomes. This is partially because disentangling which occupations count as STEM from the Census Occupational Code is already difficult, let alone sorting them into 'support' and 'professional', without attempting to further refine the categories. For practical purposes, most studies tend not to bother attempting to separate them, as STEM skills, especially in mathematics, tend to be broadly transposable and widely applicable to fields outside of their immediate domains.

For the purpose of this study, variables using occupational codes were drawn from variables constructed by the authors of the original LSAY study, in which codes had already been identified as STEM professional, STEM support/technical, and non-STEM. Social sciences were not included as STEM. For the student expectations variable 'student expects STEM (when 40)', the occupational codes were matched against the tables of STEM professional, STEM support/technical, and non-STEM in the constructed variables. All occupational codes in the study were drawn from the 1970 Census Occupational Codes, including those on the 2007-2011 series of questionnaires. This was for consistency, as those were used in the original questionnaires of the 1980s, but with the caveat that as technology and science have evolved since 1970, it is possible the job titles and functionalities have as well, and so may not be perfect matches conceptually.

Contribution and Practical Implications

Career aspirations are formulated in adolescence, and largely influenced by perceived individual competencies and values (Tai et al, 2006). As most STEM fields have a rather inflexible prescribed curriculum, it is difficult to begin a STEM pathway after the first year of college; thus it is important to identify the factors in secondary school that will predict later college and career choice. As research has shown that many students have already decided whether to pursue STEM or not by Grade 12 (Maltese and Tai, 2011; Wang, Degol, & Ye, 2015), examining the trajectories of relevant factors is key to designing effective interventions.

The motivational belief factors behind both STEM career choice and successful attainment of STEM careers are complex but arguably more predictive than academic achievement or course enrollment (Eccles, 2009; Maltese and Tai, 2010, 2011; Wang & Degol, 2013). Identifying subgroups of developmental change in these factors over the middle and high school grades is an important contribution to enabling a better understanding of whether the timing of interventions matters in relation to pursuing actual STEM careers. The current study clearly identified a class of students for whom the perceived utility of science decreased over the lower grades but increased during high school, and another for which it increased over the lower grades but plateaued immediately upon entrance to high school. That this failed to be relevant to most college and career outcomes suggests that encouraging interest and engagement in science and science careers is only one component of setting students up for persistence in the STEM pipeline. The uncovering of a class of students for whom science-specific self-concept decreases over time and a class for which it increases is interesting in that the initial mean for the Increasing class is much lower than the Regular class or the Decreasing class, but is still associated with the more desirable science achievement, college, and career outcomes. Membership in the class of Increasing Science Self-Concept was the only significant predictor of successfully attaining a professional STEM career. Additionally, both the respective incline and decline for the Increasing and Decreasing classes are much steeper over the middle school years, indicating a time of greater change where intervention might be beneficial. The same is true for the perceived utility of science curves, and might possibly be related. While the need to target student interest and engagement in STEM has been widely recognized, there is some indication that a greater focus on development of self-perception and motivational factors and their relationship with achievement and persistence would not be ill-advised.

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