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High School Students' Math and Science Motivation Profiles: Stability and Relationship With Their Stem Career Aspirations

Jiali Zheng

HIGH SCHOOL STUDENTS' MATH AND SCIENCE MOTIVATION PROFILES: STABILITY AND RELATIONSHIP WITH THEIR STEM CAREER ASPIRATIONS

by

Jiali Zheng

Bachelor of Arts
China University of Petroleum, 2003

Master of Arts
Beijing Foreign Studies University, 2010

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Accepted by:

Matthew Irvin, Major Professor

Angela Starrett, Committee Member

Melissa Duffy, Committee Member

Dexin Shi, Committee Member

Tracey L. Weldon, Interim Vice Provost and Dean of the Graduate School

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ABSTRACT

Motivation to study mathematics and science is an important influencing factor of career aspirations in STEM fields which predicts STEM major choice in college and STEM careers after graduation. Using restricted data from a nationally representative sample HSLS:09, the current study identified U.S. high school students' motivation profiles in mathematics and science courses in 9th and 11th grade, examined the stability of these profiles across the two time points, and studied the association between 11th grade motivation profiles and STEM career aspirations. Differences between male and female students in motivation profiles, profile stability and career aspirations were examined. The stability of STEM career aspirations between 9th grade and 11th grade and the consistency between 11th grade STEM career aspirations and STEM major choice in college were also investigated. Latent profile analysis revealed four distinct motivation profiles at both time points. Latent transition analysis found substantial stability in profiles: participants were most likely to stay in their original profiles than transition to another profile. Students in the *High All* profile in 11th grade were more likely to aspire for STEM careers and health occupations than those in other profiles. Students in the *Higher Science* profile were more likely to aspire for health occupations than those in the *Higher Math* profile. There were significant differences between male and female students in profile membership, transition probability, and STEM career aspirations. In general, male students were more likely to be in latent profiles characterized by higher math and science motivation and aspire for traditional STEM careers. Female students

were more likely to be in profiles characterized by lower motivation and aspire for health occupations. Career aspirations remained relatively stable from 9th grade to 11th grade. About 70% of students had the same career aspirations in 11th grade as in 9th grade. About 62.5 % of the participants' first major in college was consistent with their career aspirations in 11th grade. Implications of these results for research and interventions on math and science motivation and STEM career aspirations are discussed.

Keywords: STEM, math motivation, science motivation, career aspiration, person-centered approach

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AIC………………………………………………………… Akaike Information Criterion

ANOVA…………………………………………………………...Analysis of Variance

BIC……………………………………………………...Bayesian Information Criterion

EVT………………………………………………………… Expectancy-Value Theory

LCA……………………………………………………….…Latent Class Analysis

LMR………………………………………………………… Lo-Mendell-Rubin Test

LPA………………………………………………………...Latent Profile Analysis

LRT……………. ………………………………………………...Likelihood Ratio Test

LTA…………………………………………………………Latent Transition Analysis

OR……………………………………………………………………………Odds Ratio

SABIC……………………………………………………… Sample-size Adjusted BIC

STEM………………………………Science, Technology, Engineering, and Mathematics

CHAPTER 1

INTRODUCTION

Many countries urgently need a workforce for Science, Technology, Engineering, and Mathematics (STEM) to help address their increasingly volatile economy (Razali, 2021). Therefore, students' STEM career/occupational aspirations, which may play a crucial role in bolstering the STEM pipeline and workforce, have received increasing attention worldwide. Career aspirations are based on individual aptitudes, interests, and values. Research has consistently demonstrated that STEM career aspirations shape subsequent pathways to the STEM career pipeline (Eccles, 2009; Eccles et al., 2004; Maltese & Tai, 2011; Wang, 2012). For example, high school career plans predict college major, STEM degree completion (Maltese & Tai, 2011; Morgan et al., 2013; Tai et al., 2006), and having a STEM career as an adult (Lauermann et al., 2017). As students' attitudes towards STEM careers usually stabilize and level during their secondary years (Wiebe et al., 2018) and occupational interest remains stable during much of adolescence (e.g., Low et al., 2005), it is important to closely examine the factors influencing adolescents' STEM career aspirations.

Though research has found that students with higher prior mathematics and science ability or achievement were more likely to aspire for STEM careers, choose STEM majors in college, or have future STEM employment (e.g., Holmes et al., 2018; Sahin et al., 2018; Wang et al., 2017), having high ability may not always be sufficient to

motivate their pursuit of a STEM major or occupation (Ceci & Williams, 2010; Maltese & Tai, 2011, Wang et al., 2017). For instance, some studies found that science ability has no direct effect on students' motivation to aspire to a science career in the future; instead, science ability belief is positively associated with their motivation to become scientists (Taskinen et al., 2013). High school students with relatively low math and science abilities were more likely to have a STEM career in the future if they had higher math ability self-concept (Wang et al., 2017). Therefore, ability beliefs, such as self-efficacy and ability self-concept, could be a more important predictor of career choice decisions than achievement, at times or for some youths (Bandura et al., 2001; Eccles, 2005). Meanwhile, students with high levels of skill and preparation in math and science may not aspire for and choose STEM careers or choose STEM majors unless they are very interested in STEM (e.g., Lubinski & Benbow, 2006; Maltese & Tai 2011; Masnick et al., 2010). This is because students must value STEM to be motivated to pursue it (Andersen & Cross, 2014; Maltese & Tai, 2011). Motivational beliefs, such as competence beliefs, interest in, and perceived utility value of math or science courses, are positively associated with students' willingness to pursue a STEM career (see Wang & Degol, 2013 for a review). Fostering students' motivation in math and science courses could increase their desire to choose STEM fields (Aeschlimann et al., 2016; Rosenzweig & Wigfield, 2016). Therefore, it is necessary to closely examine how key math and science motivational beliefs influence STEM career aspirations.

Researchers have generally used variable-centered approaches (e.g., regression, ANOVA, or structural equation modeling) to examine the relationship between academic motivation and career aspirations (Paixão & Gamboa, 2017). Variable-centered

approaches are designed to examine average relations between variables in a given sample or each variable's unique contribution to an outcome (Moran et al., 2012; Vansteenkiste et al., 2009). However, individual students often hold multiple motivational beliefs simultaneously (e.g., Andersen & Chen, 2016; Conley, 2012; Linnenbrink-Garcia et al., 2018), and these motivational factors may work together to influence students' STEM-related decisions (Perez, Wormington, et al., 2019). Therefore, it is not sufficient to only study how each motivational variable individually predicts STEM outcomes with variable-centered approaches. Further, research finds that although expectancy beliefs, task values, and costs are theoretically distinct variables, they are interrelated (Perez, Dai, et al., 2019). Such interrelation can pose difficulty for variable-centered statistical analyses. For instance, some studies have examined the interactive effects of science expectancy and value beliefs on STEM career choice (Nagengast et al., 2011), but it is challenging to examine interactions between more than two variables and clearly describe the joint effects of the variable combinations with variable-centered approaches (Gillet et al., 2017; Perez, Wormington, et al., 2019). There might be too many interactions to interpret when more variables are involved. Besides, some interactions may occur very rarely, therefore, are not worth analyzing. Person-centered approaches that consider how typical combinations of beliefs influence behavior are more appropriate to model complicated relationships. Person-centered approaches, such as latent class/profile analysis, can identify frequently occurring combinations of motivational beliefs within a sample and how these combinations predict distal outcomes.

Due to various reasons, differences between males and females in STEM fields have been evident in the past decades. Although females have made impressive progress

in math and science course enrollment and performance in recent years, there are still concerns about the number of females pursuing degrees and careers in specific STEM fields (National Science Foundation, 2008, 2011). Studies have also found that male adolescents were more likely to be interested in a STEM career or pursue a STEM major (e.g., Holmes et al., 2018; Jiang et al., 2020)[1]. It is worth noting that gender differences in occupational interests vary greatly by STEM fields, with men much more interested in physical sciences, mathematical careers, engineering disciplines, and women more interested in social sciences and biological/medical services (Su & Rounds, 2015; Watt et al., 2017; Wiebe et al., 2018). Distinguishing between STEM fields in which women are well-represented (Health, Biological, and Medical Sciences; HBMS) and those in which women are not (Mathematics, Physical, Engineering, and Computer Sciences; MPECS) can be a meaningful strategy to investigate gender differences in STEM career choices (Eccles & Wang, 2016). Compared to prior achievement, differences in math and science enjoyment and self-concept explain a much larger variance in the gender gaps in high school students' STEM career aspirations and females' uneven representation in STEM career choices (Riegle-Crumb et al., 2012; Wegemer & Eccles, 2019). Therefore, some researchers point to individual motivation in math and science as a more important explanatory factor for the observed lack of female participation in STEM fields (Shumow & Schmidt, 2013; Taskinen et al., 2013). Research findings further indicate that although girls in high school are less likely to be interested in some STEM majors, such as physics,

[1] Many existing research studies have examined gender differences in career aspirations. However, gender and sex have been used interchangeably in some of these studies. For instance, some studies examine "gender differences" between "males and females" based on the sex assigned at birth (usually obtained from school record instead of self-reported gender identity). The literature review keeps the original wording from the reviewed literature.

computer science, engineering, and energy (Gremillion et al., 2019), those who do choose a STEM major are as likely to earn a STEM degree as men (e.g., Cech et al., 2011; King, 2016; Ost, 2010; Soldner et al., 2012). Therefore, motivating girls in high school to be interested in STEM careers becomes a critical first step towards improving their STEM representation.

Considering the critical role of math and science motivational beliefs in STEM career aspirations and the necessity of using person-centered research methods, the primary purpose of the current study is to investigate high school students' math and science motivation profiles as well as the stability of motivation profiles, and how motivation profiles relate to their career aspirations in STEM fields. Considering the gender differences in STEM career aspirations and motivational beliefs, a secondary purpose is to examine differences between male and female students in math and science motivation profiles, profile stability, and how those differences affect their STEM career aspirations.

1.1 THEORETICAL FRAMEWORK

Expectancy-value theory (EVT) (Eccles et al., 1983) provides one of the most comprehensive theoretical frameworks for studying individual and gender differences in mathematics and science academic motivation, performance, and career choice (e.g., Eccles, 1994, 2005; Wigfield & Eccles, 2000). EVT posits that *expectancies for success* and *subjective task values* are the most proximal psychological determinants of essential outcomes, such as academic choice and persistence (Eccles, 1983; Wigfield & Eccles, 2000).

Expectancies for success refer to individuals' beliefs about how well they will perform on an upcoming task (Eccles & Wigfield, 2020). Subjective task values refer to

the motivation that allows an individual to engage in an activity (Eccles, 1983). Subjective task values are further divided into intrinsic value (interest or enjoyment), attainment value (importance for identity or self), utility value (usefulness or relevance), and cost (loss of time/valued alternatives, overly high effort demands, or negative psychological experiences such as stress) (Eccles & Wigfield, 2020). Expectancies for success and subjective task values are usually domain-specific and are affected by individuals' personal characteristics, interpretations of their own past achievement experiences, social experiences, and cultural norms (Eccles, 1983; Eccles, 1994; Eccles et al., 1997; Eccles & Wigfield, 2002).

1.2 PERSON-CENTERED APPROACHES

Person-centered approaches focus on identifying homogeneous subgroups of participants who share similar behavior patterns by categorizing individuals into distinctly different groups based on patterns that appear across a variety of variables (Hayenga & Corpus, 2010). Therefore, individuals who function similarly and differently from other individuals at the same level are classified into different groups. Interpreting profiles of multiple beliefs is usually less challenging than interpreting complex interactions that involve multiple variables produced in variable-oriented analyses. By identifying common combinations of variables that represent individuals in a given sample, one can also avoid the concern about interpreting aspects of the interaction that rarely occur in the sample (Bergman & Trost, 2006; Wormington & Linnenbrink-Garcia, 2017).

1.3 GAPS IN LITERATURE

EVT posits that expectancy and value beliefs are domain-specific (Eccles, 1983), and studies found that motivation is not a static trait of the learner, as it may vary from course to course (e.g., Ng et al., 2016). STEM includes both math and science domains. However, most of the research has only examined either motivation in math (e.g., Jiang et al., 2020; Lauermann et al., 2017) or motivation in science (e.g., Nagengast et al., 2011) as the predictor of STEM career aspirations. Studies that do include both math and science motivation usually examine students' math and science motivational beliefs in separate analyses (Andersen & Cross, 2014), or use a composite score averaged across math and science (e.g., Garriott et al., 2013). Only a few have examined how math and science abilities and interests interactively predict STEM career choices (e.g., Garriott et al., 2017). Scholars have argued that using adolescents' motivational beliefs in a single domain to understand their STEM choices is insufficient to understand their STEM pathways development (Wang & Degol, 2017). This is because although correlations between high school students' math and science achievement scores tend to be moderately high, correlations between math and science expectancies and interests are low (Else-Quest et al., 2013; Li et al., 2002).

Variable-centered approaches have examined individual and interactive effects of different predictors on STEM career aspirations, but they primarily focus on main effects (and sometimes interaction effects) rather than the effects of complex combinations of variables (Perez, Wormington, et al., 2019). Person-centered analyses may be more appropriate to examine how motivation profiles shape academic choices, such as STEM career aspirations and STEM major choice, as multicollinearity issues do not exist in person-centered approaches such as latent profile analysis (Perez, Dai, et al., 2019). A

few studies have used person-centered approaches to examine within-person and within-sample stability of motivation profiles over time, guided by self-determination theory (Paixão & Gamboa, 2017; Gillet et al., 2017) and achievement goal theory (Goncalves et al., 2017; Tuominen et al., 2020). However, up to now, few studies have examined the math and science motivation profiles characterized by expectancies and values. Furthermore, most of the studies on motivation profiles are cross-sectional and have not adequately examined the critical issue of profile stability (Gillet et al., 2017). Besides, gender differences in math and science academic profiles and how the differences influence STEM career aspirations have not been thoroughly investigated. More research is also needed to explore gender differences in the stability of math and science motivation profiles.

To address these research gaps, the present study uses person-centered approaches (latent profile analysis and latent transition analysis) to identify high school students' math and science motivation profiles in 9^{th} and 11^{th} grade, examine stability of these profiles across the two time points, and investigate whether math and science motivation profiles would be differentially related to aspirations in traditional STEM occupations (e.g., physical science, information technology, electronic engineering, and mathematics) and health occupations (e.g., physicians, veterinarians, nurses, medical technicians). Differences between male and female students in motivation profiles and profile stability, and how the differences influence STEM career aspirations are examined along the way. The study also descriptively examined stability of STEM career aspirations and the association between STEM career aspiration in high and STEM major choice in college.

1.4 SIGNIFICANCE OF THE STUDY

Studies have shown that adolescents' career aspirations are highly stable from early adolescence to middle adulthood (see Low et al., 2005 for a review of career interest stability). By 12th grade, the decision to major in a STEM or non-STEM career was largely solidified for many students (Maltese & Tai, 2011). Therefore, the high school years are critical for identifying the cognitive and motivational factors that increase the likelihood of future STEM employment (Wang et al., 2017). Research has confirmed that in order to improve students' learning, one of the most critical factors that educators can target is their motivation (Williams & Williams, 2011). The current study used a nationally representative sample to study high school students' STEM career aspirations, which will contribute to our understanding of how motivation in math and science influences STEM career aspirations.

The current study is one of the few studies that examine latent profiles of high school students' academic motivation in math and science courses under the EVT framework. A study that examines how math and science motivation jointly influences STEM outcomes seems timely and necessary given that limited prior research has investigated such a question. Findings will contribute to our understanding of how math and science motivational beliefs may coexist and what combinations of these variables may be adaptive or deleterious for career aspirations in STEM (Perez, Wormington, et al., 2019). Such an understanding can provide insights into identifying high school students who might join in STEM disciplines. Moreover, differences in motivation profiles between male and female students are examined to determine whether students of a particular sex were overrepresented in profiles characterized by lower math or science motivation.

Besides, exploring the stability of math and science motivation profiles will help understand how adolescents' career trajectories are developed. The current study uses a longitudinal design to address within-person profile stability (the stability in the academic motivation profiles of individuals) and within-sample profile stability (whether the nature of the academic motivation profiles changes across time) (Kam et al., 2016) in high school, which helps to better understand motivation profile stability. Such an understanding could guide school and career counselors to create targeted and relevant career development interventions that aim to increase the number of high school students who plan to select a STEM career path.

Taxonomies of STEM occupations usually include physical and natural sciences, computer science, technologist positions, engineering, and mathematics. There is ongoing debate on whether to consider social sciences and medical/health sciences as STEM occupations (Wiebe et al., 2018). The current study considers health occupations and social sciences[2] as STEM subdomains and treats health occupations separately from traditional STEM domains when studying associations between motivation profiles and career aspirations. Distinguishing between health occupations and other STEM domains is desirable because many students aspire for a health occupation in this sample of students. It could help us better understand the association between motivation profiles characterized by different levels of math and science motivations and career aspirations in different fields (non-STEM, traditional STEM, and health occupations). Further, it could also help better understand gender disparity in different STEM fields, as research finds that female representation is uneven across STEM fields (Wegemer & Eccles,

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[2] Social sciences were coded as "split across two (STEM) domains" and its relation with math and science motivation profiles was not examined due to its small sample size and ambiguous coding.

2019). For instance, female adolescents favored human services occupations such as social science and health occupations. Male adolescents, on the other hand, were more likely to aspire to math/science-related careers (Lauermann et al., 2015). The findings may provide insight into understanding the imbalance between male and female students in different STEM occupations.

Specifically, the current research extends the literature on high school students' motivation profiles and STEM career aspirations by:

1. using a large, restricted, nationally representative longitudinal dataset and person-centered approaches to examine motivation profiles characterized by both mathematics and science motivational beliefs;
2. examining both within-sample and within-person motivation profile stability;
3. examining how math and science motivation profile and STEM career aspirations are associated;
4. making a distinction between traditional STEM occupations and health occupations when examining their association with motivation profiles;
5. investigating differences between males and females in math and science motivation profiles, profile stability, and how that influences career aspirations in different STEM fields.

CHAPTER 2

LITERATURE REVIEW

2.1 EXPECTANCY VALUE THEORY OF MOTIVATION

Expectancy-Value Theory (EVT; Eccles et al.,1983; Eccles, 2005) offers a comprehensive theoretical framework to explain achievement-related choices. EVT was initially used to explain gender differences in enrollment in advanced mathematics and science classes and the pursuit of college majors and careers in mathematics and science. It focuses on belief systems and cultural and gender-related differences in current levels and changes in individuals' competence beliefs and value beliefs (Eccles, 1994; Eccles & Wigfield, 2002). EVT posits that beliefs about how well individuals will do on the task (expectancy) and the extent to which they value the task (value) will influence their choice, persistence, and performance (e.g., Wigfield & Eccles, 2000). Expectancies for success include ability beliefs and expectancy beliefs. Ability beliefs are an individual's current beliefs about being able to complete a task, which are general beliefs about competence in a specific domain. Expectancy beliefs are beliefs about being able to do the task in the future (expectancies of success on a particular upcoming task). However, the two sub-components are often highly correlated and difficult to distinguish in empirical research; therefore, they have typically been used interchangeably or collapsed into a single construct (Eccles & Wigfield, 2002).

Expectancies for success are theoretically closely related to other conceptions of self-beliefs, such as self-efficacy in social cognitive theory (Bandura, 1997). In prior

research that adopted EVT as the theoretical framework, similar constructs have been used interchangeably with expectancies, such as self-efficacy, competence belief, self-concept of ability, or confidence to successfully complete tasks in a specific domain (e.g., Andersen & Chen, 2016; Andersen & Ward, 2014; Neuville et al., 2007; Schaefers et al., 1997). Some studies which claimed using EVT as their theoretical framework used self-efficacy beliefs to represent expectancies for success (e.g., Neuville et al., 2007; Schaefers et al., 1997) because expectancy beliefs were measured like self-efficacy expectations (Eccles & Wigfield, 2002). Self-efficacy is an individual's belief in his/her ability to succeed in specific situations or accomplish a task (Bandura, 1982). A high correlation was also found between self-efficacy and expectancies (Jones et al., 2010); therefore, it makes sense for some studies to use self-efficacy.

Subjective task values refer to the motivation that drives an individual to engage in an activity (Eccles, 1983). Four types of task values have been identified: intrinsic value, attainment value, utility value, and cost (Eccles, 2009; Eccles et al., 1983). Intrinsic value is sometimes referred to as interest/enjoyment value, which reflects the inherent enjoyment or interest that individuals experience from engaging in the task of the subject in question. Attainment value is the perceived importance of a task for an individual’s identity and self-worth. Individuals will attach a high value to options that allow them to establish this identity (Eccles, 2009). Utility value reflects the perceived usefulness or importance of a task in helping to accomplish other goals. Cost is related to perceptions of drawbacks when engaging in a task, and it is essential for decision-making (Eccles et al., 1983). Eccles and Wigfield (2020) suggested three different types of costs: effort cost (excessive effort demands), opportunity cost (loss of time or valued

alternatives), and emotional cost (negative psychological experiences such as anxiety and the social costs of failure). Partly due to its complex multidimensional nature, cost has been operationalized less fully until recently, and thus studied less comprehensively than intrinsic value and utility value.

Theoretical work (Eccles, 1983) and empirical studies (e.g., Nagengast et al., 2011) suggest that expectancies and values interact to predict important outcomes, such as academic achievement, continuing interest, and choice. EVT posits that one's ability self-concept influences interest in a given field (Eccles, 1983). On the other hand, high school students' math interest was a positive predictor of their math identities (e.g., Godwin et al., 2016). Caspi and colleagues (2019) found high correlations between nineth graders' self-efficacy, attainment value, intrinsic value, utility value, and relative cost in terms of picking STEM disciplines in high school. In much of the empirical research on task values, the three subconstructs of task values (intrinsic, utility, and attainment) have not been measured separately (e.g., Aschbacher et al., 2014; Bong, 2001; Neuville et al., 2007; Perez et al., 2014). This is perhaps because intrinsic, utility, and attainment value are sometimes positively correlated with each other (e.g., Beier et al., 2019), and attainment value and intrinsic value are often highly correlated (Hulleman et al., 2008; Trautwein et al., 2012). However, it is not always the case. For instance, high school students who feel competent in math and who value math as useful are not necessarily interested in math (Lazarides et al., 2020), which suggests the necessity to study the value components separately.

2.2 ASSOCIATIONS BETWEEN EXPECTANCIES, VALUES, COST, AND STEM CAREER ASPIRATIONS/STEM MAJOR CHOICE

Existing studies that used variable-centered approaches have found unique relations between expectancies, task values, perceived costs, and STEM outcomes, such as STEM career aspirations and STEM major choice in college. For instance, ninth-grade competence beliefs, intrinsic value and utility value in math positively predicted career goals related to math in 12th grade (Lauermann et al., 2017). High school students' science expectancy and value also predicted STEM career interest (Robnett & Leaper, 2013). Riegle-Crumb et al. (2011) found that eighth graders' science self-concept and enjoyment are positively and significantly associated with science career aspirations after controlling for the effect of test scores, while math self-concept and enjoyment do not help explain differences in career aspirations. It is probable that other aspects of the EVT model, such as attainment value or utility value, may be more pertinent. Responses to open-ended questions reveal that interest, utility value, and self-efficacy were the three major reasons most frequently cited by nineth grade students who plan to choose a STEM discipline in high school; while they only occasionally cited reasons such as attainment value, friends and family (Caspi et al., 2019). However, although research findings indicated that both expectancies and task values predicted achievement-related choices, such as career interests, they also suggested that expectancies was an important predictor of achievement among high school students (Hill et al., 2010), while task values can be more influential in shaping individual career choices than academic self-concept (Wigfield & Eccles, 1992; Wigfield et al., 2009). Gender differences have been found in expectancy and value beliefs in math and science. For instance, high school boys had higher math task values, and a greater preference for STEM careers (Wang et al., 2015).

Meanwhile, high school girls were more likely to have lower math self-efficacy/self-concept and values, which predicted a lower likelihood for them to strive for a STEM career, such as math (Dang & Nylund-Gibson, 2017; Guo, Parker, et al., 2015; Lazarides & Lauermann, 2019).

Expectancies or self-efficacy is domain-specific, and individuals are more willing to be involved in activities in which they feel they can succeed (Eccles et al., 1998). Middle school and high school students' mathematics-related ability beliefs, such as mathematics self-efficacy and expectancy for success, strongly predicted their later aspiration to a STEM career, such as math, science, and engineering (Blotnicky et al., 2018; Cass et al., 2011; Lauermann et al., 2017; Mau, 2003; Seo et al., 2019). High school students' math self-efficacy beliefs affected students' intent to major in STEM fields, which in turn influences entrance into STEM majors (Wang, 2012). Wegemer and Eccles (2019) found that math self-concept of ability became a salient predictor of STEM choices in 11th grade. Science self-concept affected 9^{th}-grade students' interest in science-related careers (Taskinen et al., 2013), and science efficacy predicted 9^{th} graders' career aspirations in STEM fields (Mau & Li, 2018). Math and science ability beliefs are sometimes measured together as a single variable. For instance, students in 9^{th} grade who had higher math and science efficacy were more likely to consider selecting a STEM major in college (Sahin et al., 2018). High school students' math/science self-efficacy was a significant predictor of math/science interests which predicted math/science career goals (Garriott et al., 2017). This finding suggests that sometimes the relationship between efficacy and career interest might be mediated by math/science interests. Different expectancy levels could also be associated with interests in various STEM

careers. For instance, students with lower math self-concept of ability in middle and high school were more likely to be interested in careers in HBMS (Health, Biological, and Medical Sciences) over MPECS (Mathematics, Physical, Engineering, and Computer Sciences) (Wegemer & Eccles, 2019).

Perhaps one of the prominent factors that hinder girls from aspiring to careers in STEM fields is low self-efficacy or ability belief in math and science. For instance, boys in eighth grade had higher math efficacy than girls, and they were more likely than girls to persist in science and engineering career aspirations (Mau, 2003). Female high school students had lower math and science self-concept of ability and were less likely to pursue a STEM major in college (Jiang et al., 2020). Interestingly, high-school boys perceived higher math competence than girls even when their grades and test scores in math were similar and were more likely to have math related career aspirations (Correll, 2001). Furthermore, math self-concept was more important for female adolescents than male adolescents in their career choices related to STEM (Watt et al., 2017).

Research finds that expectancies or efficacy belief is a necessary but not a sufficient predictor of adolescents' educational outcomes or career choices (Wang, 2012). Being competent at an activity does not necessarily mean that an individual will enjoy that activity (Wang & Degol, 2013). EVT suggests that besides the confidence in one's abilities to succeed in such activities, career aspirations also depend on the value one attaches to various occupation-related activities (Wang & Degol, 2013).

Values are concerned with preferences and desires (Perez & Wormington et al., 2019). Intrinsic value (operationalized as interest and enjoyment) has been studied very frequently in relation to STEM outcomes. Mathematics interest is a significant predictor

of underrepresented high school students' career aspiration in STEM fields (Cass et al., 2011; Mau & Li, 2018). Nineth graders with higher levels of interest and enjoyment in science reported having a higher motivation to take up a science-related occupation, even after class-level characteristics were controlled for (Taskinen et al., 2013). Science enjoyment is still a significant predictor of fifteen-year-old students' STEM career aspirations after controlling for science achievement and STEM career awareness (Ahmed & Mudrey, 2019). Students in 7th and 9th grades who were more interested in scientific and technical skills were more likely to consider a STEM career (Blotnicky et al., 2018). Conversely, a few studies did not find a significant influence of intrinsic value on STEM career interest. For instance, Watt and colleagues (2012) found that adolescents' intrinsic value in math did not predict math-related career plans in U.S. or Canadian samples (Lauermann et al., 2017). Researchers have found that mathematics interest played the most substantial role in predicting male high school students' STEM career preferences, and it was more important for male adolescents than female adolescents in their career choices related to STEM fields (Watt et al., 2017).

Subject-specific identity (e.g., math identity, science identity, or STEM identity) is often used to represent attainment value (e.g., Estrada et al., 2018; Kuchynka et al., 2019; Leggett-Robinson et al., 2018). A high correlation has been found between attainment value and subject-specific identity (e.g., Jones et al., 2010), which can justify the use of identity in place of attainment value. Research asserts that students who have higher subject-related identities are more likely to aspire for related careers. For instance, a student with a high science identity was more likely to follow the norms of that role and pursue a career in science (Estrada et al., 2011; 2018). High school students' math

identity was important for predicting choosing an engineering major at college (Godwin et al., 2016). Higher math and science attainment values were significantly related to increased odds of high school students' planning for a STEM career (Gottlieb, 2018). Given the potential value of math and science identity in pushing high school students into or out of the STEM pipeline (Wang & Degol, 2013), studying how math and science identity predict career aspirations in STEM is necessary.

Utility value concerns how the task relates to future goals. If an activity is instrumental to pursuing their goals or is integral to their vision of their future, students may be motivated to pursue it, even when they do not enjoy it (Wigfield, 1994). Math utility beliefs positively predicted high school students' aspirations in a math-related career (Lauermann et al., 2017). Higher levels of perceived math utility significantly increased high school students' odds of planning for a STEM career (Gottlieb, 2018). Math utility value was more directly related to 15-year-old Australian youths' STEM major selection compared to math self-concept (Guo, Parker, et al., 2015). Similarly, high school students' belief that science was useful for learning, career, and everyday life was a significant predictor of engineering career choice (Godwin et al., 2016). Science instrumental value (utility value) was an important predictor of 15-year-old students' career aspirations after controlling for science achievement, STEM career awareness, and socioeconomic status (Ahmed & Mudrey, 2019). Watt et al. (2019) examined mathematics and science utility value together, and found it was positively associated with 10th graders' effort exertion and STEM career aspirations.

Cost has been studied much less frequently as a predictor of STEM outcomes. Existing studies found that adolescents might not choose to pursue a career in

mathematics or science if they perceive that the effort cost is too great (Wang & Degol, 2013). High school students who did not perceive a high time or social cost to study math or science classes were more likely to plan for a career that requires a bachelor's degree, regardless of the career type (Gottlieb, 2018).

Expectancies and values are distinct constructs, but they are correlated in the meantime. For instance, high school students' self-concept of ability and subjective task value were moderately correlated within math and science (Jiang et al., 2020). Besides, 9^{th} graders' expectancies tend to predict their later task values, such as intrinsic interest (Taskinen et al., 2013), which means individuals tend to value the subjects/tasks in which they feel competent (Eccles & Wigfield, 2002). A few studies have examined interactions between these motivational variables and how different combinations influence STEM outcomes. For instance, Nagengast et al. (2011) found that 15-year-old's science expectancy, science intrinsic value (enjoyment of science), and the expectancy × value interaction all had significant and positive effects on intentions to pursue scientific careers. Trautwein et al. (2012) found that if either expectancies or values was very low, the other cannot compensate for it. High scores on the outcome variables could only emerge when both expectancy and value beliefs were high. In a nationally representative longitudinal sample of Australian high school students, math self-concept was more strongly related to choosing STEM fields of study when the intrinsic value was also high (Guo, Parker, et al., 2015). These findings suggest that it is crucial to simultaneously consider the levels of both competence beliefs and task values. It is worth noting that most studies only examined two-way interactions between competence beliefs and values (as a single construct)/each subcomponent of task values individually. As a result, it is

not clear how different levels of the subdimensions of task values and competence beliefs are combined and how such combinations relate to key STEM outcomes.

2.3 PERSON-CENTERED APPROACHES AND FINDINGS

Individual differences are essential to the field of educational psychology because we cannot assume that each individual learns in the same way under the same conditions (Raufelder et al., 2013). However, our knowledge about individual differences in educational psychology is limited because of the dominance of variable-oriented statistical analyses, which assume equality between individuals, and a seeming reluctance to employ person-oriented methods (Rosato & Bear, 2012). Fortunately, person-centered approaches have been gaining momentum in recent research in educational psychology.

The term "person-centered" is often used interchangeably with "pattern-oriented" and "person-oriented" (Bergman & Andersson, 2010). So far, there is no unified definition of a person-centered approach. The works of Bergman and Magnusson have heavily influenced the theory and methodology of person-centered approaches developed over the past thirty years (e.g., Magnusson, 1988; Magnusson & Törestad, 1993; Bergman & Magnusson, 1997; Bergman, von Eye, & Magnusson, 2006). The theoretical conceptualizations of the person-oriented approach are grounded in the holistic-interactionistic framework, in which the individual is seen as an organized whole, functioning and developing as a totality formed by interactions among the components involved (e.g., biological factors, plans, values, goals, behaviors, and environmental factors) (Magnusson & Törestad, 1993; Bergman & Magnusson, 1997; Bergman & Wångby, 2014). In operation, this focus usually involves studying individuals based on their patterns of individual characteristics that are relevant to the problem under investigation (Bergman & Magnusson, 1997).

Person-oriented research acknowledges that particular concepts exist in or only apply to specific populations or even individuals. This basic tenet of person-oriented approaches allows for the use of terms that are specific to populations, age groups, locations, or historical times in the formulation of person-oriented theories (Bergman & Magnusson, 1997; Bergman, von Eye, & Magnusson, 2006; von Eye & Bergman, 2003). Another fundamental tenet asserts that aggregating data prematurely can lead to conclusions that fail to recognize the variability in populations (von Eye & Spiel, 2010). Bergman and Wångby (2014) proposed some more revised tenets. They argued that individuals' development process follows laws that relate to structures functioning as patterns of operating factors. These laws are supposed to have communalities across individuals but not identical across individuals. Besides, in the development process, typical patterns of observed system components often show up both within the individual and across individuals.

The person-oriented theoretical view has implications for the choice of research methodology in empirical research: the methodology should allow for inferences about the single person and individual patterns of functioning. Usually, this can only be attained by treating the key pattern defining the system of interest (usually a vector of variable values) as an indivisible unit in the analysis (Bergman & Wångby, 2014). This is different from a standard variable-oriented approach, which focuses on the variable as the primary unit of analysis. The main theoretical and analytical unit of a person-oriented approach is the specific pattern of operating factors (Bergman & Wångby, 2014). In other words, the individual and the pattern are at the focus of person-oriented approaches. Although theoretically, there is an infinite variety of differences in observed states and

process characteristics at a specific level, there is often a small number of more frequently observed patterns/common types if viewed at a more global level (Bergman & Magnusson, 1997). There are two major kinds of person-centered analysis approaches: 1) algorithmic approaches, which include the traditional “cluster analyses,” and 2) latent-variable approaches, which are methods based on latent-variable models. Latent class analysis (LCA) is a latent-variable approach that is used in the current study.

LCA is a type of mixture model that aims to describe subgroups of participants distinct from one another in their pattern on a number of indicators. LCA assumes that people can be classified into subgroups or subpopulations with different configural profiles of personal and/or environmental attributes with varying degrees of probabilities. These subgroups are called latent classes, which are represented in the model as the different categories of an underlying categorical latent variable. Each category represents an inferred subpopulation (Lubke & Muthen, 2007). Individuals are categorized according to the pattern of their responses, and the optimal number of latent classes is determined by comparing models with different numbers of latent classes. Depending on whether the observed variables are categorical or continuous, mixture models can take the form of latent class analysis (LCA) and latent profile analysis (LPA) (Woo et al., 2018). The rationale is the same for LCA and LPA models (Bergman & El-Khouri, 2003); therefore, the following literature review may only mention LCA.

The person-oriented approach in LCA is based on three arguments. First, there are individual differences within a phenomenon or effect, and these differences are important. Second, these individual differences occur in a logical way and can be examined through patterns. Third, a small number of patterns are meaningful and occur

across individuals (Bergman & Magnusson, 1997; Bergman et al., 2003). The overall goal of LCA is to uncover groups or latent classes of individuals who share an interpretable and meaningful pattern of responses on the measures of interest (Bergman et al., 2003; Marsh et al., 2009; Masyn, 2013). The basic principle of LCA is to group individuals with a similar profile of indicator variables into distinct classes (Vermunt & Magidson, 2002). This could be done by obtaining the probability that individuals belong to different groups based on their responses to the indicator variables (Oberski, 2016; Wang & Hanges, 2011). LCA examines the distributions of groups in the data and decides whether these distributions are meaningful (Ferguson et al., 2020). It is particularly useful for research in social sciences because shared behavior patterns within and between samples may be overlooked in variable-centered, interindividual analysis (Howard & Hoffman, 2018).

In order to make the interpretation of latent classes more relevant and meaningful, it is critical to show that class memberships bear relevant relations with crucial outcome variables (Bergman & El-Khouri, 2003; Bergman & Trost, 2006). LCA can examine typical classes within a sample and how various classes relate to specific outcomes (Bergman & El-Khouri, 2003; Bergman & Trost, 2006). Researchers usually identify subgroups of individuals who share similar patterns of variables and compare them with other subgroups, not only in terms of how the variables combine to shape the latent classes/profiles but also how those combinations are associated with predictors and outcomes in different ways (Wang & Hanges, 2011).

Another way to make the interpretation of latent classes meaningful is to show that class memberships can be replicated across samples or time points (Marsh et al.,

2009; Muthén, 2003). Classifying individuals based on cross-sectional responses is sufficient in many cases, but the researcher may want to incorporate other features in others (Woo et al., 2018). Based on specific individual developmental paths, a person may change from one group to another over time, as the boundaries of many groups are not very clear and permeable (Bergman, 1988). Changing environmental or psychobiological conditions, or a combination of the two, may also lead to changes of patterns over time (Peck & Roeser, 2003). Latent transition analysis (LTA) takes into account the process aspect and can be used to analyze long-term developmental processes in terms of patterns (Bergman & Wångby, 2014). LTA is another type of mixture model developed within the latent class analysis framework (Collins & Wugalter, 1992). It is also referred to as hidden Markov modeling, where latent classes are measured over time and individuals can transition between latent classes (Muthén & Muthén, 1998-2015). With LTA, stability and change in the latent classes at the structural and individual levels can be studied (Bergman & Wångby, 2014). LTA gives us the ability to look at how individual students stay or change from their original motivation profiles, which a latent growth curve analysis cannot do.

LTA is a longitudinal extension of LCA. It is any model that includes two or more latent class constructs informed by the same or different indicators measured at different time points. LTA is designed to model not only the latent class membership but also the frequency of transitions between classes over time (Collins & Lanza, 2009). LTA considers the dynamic nature of latent class membership by modeling movements across different membership categories across developmental levels, shifting contexts, or states (Woo et al., 2018). LTA can be used to investigate the within-sample and within-person

stability in class membership by investigating whether there are different latent classes present in the data (within-sample stability), whether individual students correspond to the same classes over time (within-person stability), as well as the nature of observed class transitions (Collins & Lanza, 2009). For instance, there might be adaptive transitions and maladaptive transitions. In LTA, two or more latent class/profile variables are measured at different time points, and the relationship between these variables is estimated through a logistic regression (Asparouhov & Muthén, 2014). The latent classes/profiles in LTA are called latent statuses because they may change over time.

In recent years, researchers have paid more attention to investigating how expectancy and value beliefs are combined in students' motivation profiles and how such profiles relate to academic STEM outcomes, such as STEM course selection, selecting a STEM major in college, and STEM career aspirations. Several research studies have examined adolescents' expectancy and value beliefs using person-oriented methods (e.g., Andersen & Chen, 2016; Andersen & Cross, 2014; Aschbacher et al., 2014; Bøe & Henriksen, 2013; Chow et al., 2012; Conley, 2012; Dang & Nylund-Gibson, 2017; Fong et al., 2021; Linnenbrink-Garcia et al., 2018; Wang et al., 2013). However, some of them did not investigate the relationship between motivation profile membership and STEM outcomes.

Three of these studies used HSLS:09 data to study high school students' math and/or science motivation profiles and STEM career aspirations and STEM major choice in college. Andersen and Chen (2016) did a latent profile analysis on high school students' motivation to study science courses and examined how profile memberships were related to STEM occupational plans. Based on four profile indicators – science self-

efficacy, science attainment value, science utility value, and science interest-enjoyment value, four latent profiles were identified: 1) *Low expectancy-value*, in which all indicators were below the mean; 2) *Typical*, in which all indicators were a little above the mean; 3) *High Self-Efficacy (HSE),* in which self-efficacy was very high, but the three value indicators were relatively low; and 4) *High Utility Value (HUV)*, in which science utility value was very high, and science attainment and interest value were above those in the HSE profile, and science efficacy below the level in the *HSE profile*. The percentage of students who planned to have a STEM occupation at the age 30 was different across each motivation profile. Students in the *HUV profile* planned to have a STEM occupation at the highest rate (45.6%), followed by the *HSE profile* (36.9%). The percentage was low in the typical profile (25.3%) and low profile (15.8%). Two limitations of this study are that it only used descriptive statistics to examine the relationship between science motivation profile and occupational plans, and they did not examine math motivation and how that would affect their interest in STEM occupations. Andersen and Cross (2014) examined math profiles and science profiles separately and uncovered four distinct math profiles and four science profiles. The four math profiles were: 1) *Typical*, all profile indicators (math efficacy, math attainment value, math intrinsic value, and math utility value) were near the mean (44%); 2) *Low*, all profile indicators were below the mean (15%); 3) *High Math Self Efficacy*, math self-efficacy was high, and the other indicators were above the mean, except for math utility value, which was average (23%); 4) *High Math Utility Value*, all indicators were high, but math self-efficacy was lower than that of the high MSE class (18%). The four science profiles were similar to the math profiles. This study did not examine the relationship between math and science profiles and STEM

career aspirations, but it uncovered that students with high ability in math or science may also have low ability beliefs and low values of the subjects. Fong et al. (2021) used a subsample of HSLS:09 data (7,237 students) to investigate 11^{th} graders' math and science motivation profiles, and how these profiles influence their STEM major choice in college. Latent profile analysis revealed five profiles: *Low Math/Low Science* (low levels of expectancy and value beliefs in math and science), *Moderate Math/Moderate Science, High Math/High Science, Low Math/High Science,* and *High Math/Low Science*. Female students were less likely to be in the *High Math/High Science* profile than in the *Low Math/Low Science* profile and the *Moderate Math/Moderate Science* profile. Students in all profiles had significantly lower odds of STEM career intentions and STEM major choice than those in the *High Math/High Science* profile.

Lazarides and colleagues (2020) examined students' math motivational beliefs (task value and ability self-concept) profiles (when they were in Grade 7 and Grade 12) and how they predicted math-related career plans and choice of math related majors in college. Four latent profiles were identified: *high motivational beliefs, medium motivational beliefs, low motivational beliefs,* and *low intrinsic value*. Students' profile membership in Grade 10 predicted their math-related career plans in Grade 12: Students who were in the *low motivational beliefs* profile reported a significantly lower level of math-related career plans than students in all other profiles. Students in the *low intrinsic value* profile and students in the *medium motivational beliefs* profile in Grade 10 both reported a lower level of math-related career plans in Grade 12 than students in the *high motivational beliefs* profile (Lazarides et al., 2020). In this study, subjective task value

was measured as a single construct with four items that reflect intrinsic, attainment and utility value components.

Some research examined how science motivation predict STEM career aspirations. Aschbacher et al. (2014) used latent class analysis to classify students in eighth and ninth grades based on their perceptions of science ability and values. Students with high science ability beliefs and high values in science were more likely to be interested in STE-M (Science, Technology, Engineering, and Medical) careers than students with other combinations, such as high value but low ability belief, high ability belief but low value, and low on both. The findings suggest that ability belief and value belief in science are equally important for STEM career aspirations, and one needs to have high levels in both to be more motivated to have a STEM career. This is similar to the finding of Trautwein et al (2012) that if either expectancies or value is low, the other one cannot compensate for it. Gender and type of STE-M field did not significantly influence the relationship between science ability beliefs and values and STE-M career aspirations.

Chow et al. (2012) examined 10^{th} graders' motivation profiles based on the three subjective task values in math, physics, and chemistry (compared to English), and identified three profiles: 1) *high math and physical science*; 2) *moderately low math and physical science*; and (3) *low math and physical science*. Boys were more likely to fall into the *high math and physical science* group and were less likely to fall into the *low math and physical science* group than girls. Students in the *low* and *moderately low math and physical science* groups had lower aspirations for physical and IT-related science

jobs that require a college degree. This study did not examine expectancy belief as a profile indicator and did not study the value subcomponents separately.

Besides math and/or science motivational beliefs, some studies also considered English/verbal ability and motivation as influential factors of STEM career aspirations. For instance, Dang and Nylund-Gibson (2017) examined latent profiles of tenth graders' math self-efficacy and attitudes (values) after classifying them into different English proficiency groups and how these profiles predicted their occupations ten years later. Four latent classes were identified: 1) *High math attitudes*, *Low math self-efficacy*; 2) *Low math attitude, High self-efficacy*; 3) *Low math attitudes, Low math self-efficacy*; and 4) *High math attitudes, High math self-efficacy*. Students with high math self-efficacy and high math attitudes were more likely to have a STEM career. Female students were more likely to have lower math self-efficacy and attitudes, which helps explain their underrepresentation in STEM fields. In this study, attitudes were measured as a single construct with items reflecting task values. Another study with German high school students examined math and English expectancy and value together and uncovered four distinct profiles: 1) *Low Math and High English*, 2) *Moderate Math and Moderate English*, 3) *High Math and Low English*, and 4) *High Math and High English*. Compared with other profiles, girls were overrepresented in the *Low Math and High English* profile. Students in the *High Math and Low English* profile were most likely to choose a STEM major, followed by students in the *High Math/High English* profile, then the *Moderate Math/Moderate English* profile, and finally the *Low Math/High English* profile. Profile membership was also a better predictor of students' choice of a STEM major than achievement and demographic characteristics (Gaspard et al., 2019). Findings of this

study suggest that including English motivation as a profile indicator helps to better understand who were more likely to choose a STEM major among those who had high math motivation beliefs.

Wang et al. (2017) studied ninth graders' probability of selecting STEM occupations by first classifying them into different verbal/math/science ability groups. Three cognitive ability groups were identified: 1) moderate math and science ability and lower verbal ability; 2) high math, science, and verbal ability; and 3) low math, science, and verbal ability. Participants of the group with low cognitive ability across all three subject domains had a meager chance of STEM employment relative to participants of the other two groups. However, it is interesting to note that youths with relatively low math and science abilities were more likely to be employed in a STEM career if they had a greater math self-concept, which again shows the importance of motivational factors. For instance, in the high math, science, and verbal ability group, those with higher science task value were more likely to select a STEM career. For youths with high ability across verbal, math, and science domains, science task value and lower altruistic values were key motivators for selecting a STEM career.

Thus, many studies using variable-centered approaches have found math and/or science expectancy and values to be critical positive predictors of STEM career aspirations and cost to be a negative predictor. There are some limitations in the existing studies. For instance, although the value variables were related, they did not always occur at the same levels. However, many studies have treated the three value subconstructs as a composite variable (e.g., Aschbacher et al., 2014; Chow et al., 2012; Dang & Nylund-Gibson, 2017) or even combined expectancy and value as a single motivational variable

(e.g., Gaspard et al., 2019). Extant research also recognized the importance of using a person-oriented approach to investigate how math and science motivation relate to STEM career aspirations STEM major choice. These studies have shown that different expectancy-value profiles can be identified across different samples, and these profiles are differentially related to STEM career aspirations. It is common to see that expectancies and values are at different levels within student subgroups. In general, students with higher expectancy and value beliefs in math and science are more likely to aspire for a STEM career. Being low in either expectancy or one of the value components (especially intrinsic value) would significantly reduce the chance of aspiring for a STEM career. Sometimes their English motivation and gender may play a role. One limitation of the studies that used person-centered approaches is that most of them did not examine the stability of the motivation profiles; therefore, they could not reveal the developmental aspects of motivation profiles.

2.3 STABILITY OF MATH AND SCIENCE MOTIVATIONS

Stability is the extent to which motivational traits are temporary or are likely to persist into the future (Locke & Latham, 2004). Motivation can be seen as stable characteristics of individuals or transient states that fluctuate in response to environmental or internal states. Expectancy Value Theory holds a developmental perspective of motivational beliefs (see Eccles & Wigfield, 2002 for an overview). Even though overall motivational decreases have been found in all school stages, such as math academic self-concept (see a review in Scherrer & Preckel, 2019), several studies found that general academic self-concept, intrinsic value, and utility values are quite stable during the upper high school years (e.g., Gottfried et al., 2001; Guo, Marsh, et al., 2015). Confidence and self-efficacy in math/science were also stable across the high school

years (Gremillion et al., 2019). Lazarides and Lauermann (2019) found that the stability of students' academic self-concept, intrinsic value and utility value in mathematics were relatively high from 9th grade to 10th grade. Studies have also found gender differences in stability of motivational beliefs. For instance, girls showed increasingly lower math ability self-concept compared to boys from middle school through high school and college (Pajares, 2005). Girls' interest in mathematics decreased while boys' interest did not change through adolescence (Koller et al., 2001).

It is necessary to specifically study the stability of motivation profiles characterized by math and science motivation beliefs to understand how that might influence STEM outcomes. According to Kam et al. (2016), the adoption of a longitudinal perspective makes it possible to assess two types of stability in LPA solutions over time: 1) the consistency of profiles over time for specific participants (within-person stability); and 2) the stability of the profile structure within a sample (within-sample stability). Only a few studies have examined the motivation profile stability of high school students. Lazarides and colleagues (2019) investigated the stability of adolescents' motivation profile in mathematics characterized by mathematics self-concept, interest (including items measuring attainment value: "Mathematics is personally important to me"), intrinsic value, and utility value. They found that motivation profile membership remained relatively stable from grades 9 to 10. Meanwhile, they also found adaptive changes in motivation profile from lower to higher levels of motivation and maladaptive changes in motivation profile from higher to lower motivation levels. Another study found that math motivation profile was relatively stable from the beginning of Grade 7 to Grade 12. The *high motivation* profile showed

substantial stability, and students in the *low motivation* profile were more likely to remain in the same profile than those in higher motivational beliefs profiles (Lazarides et al., 2020). One limitation of the above two studies is that they only relied on cross-tabulation to describe the percentages of students who stayed in the same profile and who switched to another profile. As a result, only within-sample stability was described. Within-person stability – the probability of individuals staying in the same profile or transitioning to a different profile was not described.

More longitudinal studies are needed to examine the within-sample and within-person stability of motivation profiles characterized by math and science motivational beliefs. Moreover, experimental and longitudinal research is needed to study the stability of motivation profiles, examine their predictive power over career exploration and career decision-making development, and provide a more in-depth analysis of possible between-subjects and within-person variability over time (Paixão & Gamboa, 2017).

2.4 RESEARCH QUESTIONS

Based on the gaps in the literature, the present study aims to answer the following questions using High School Longitudinal Dataset HSLS: 09:

1. What are the different profiles of high school students' math and science academic motivational beliefs at the beginning of 9th grade and the end of 11th grade? Are there differences between male and female students in motivation profiles at each time point?
2. Are students' math and science motivation profiles stable from 9th grade to 11th grade? Do the probabilities of staying in the same profile and transitioning between motivation profiles differ between male and female students?

3. How is 11th grade math and science motivation profile related to 11th grade STEM career aspirations (traditional STEM fields and Health Occupations were examined separately[3]), and do male and female students differ in STEM career aspirations within and across motivation profiles?
4. How stable are high school students' STEM career aspirations between 9th grade and 11th grade? Are students' 11th grade STEM career aspirations consistent with their STEM major choices in college?

[3] In the current study, the number of participants who picked social science as their future occupation is very small, but many picked health occupations. Therefore, it makes sense to examine differences in choosing traditional STEM or health occupations between male and female students.

CHAPTER 3

METHODS

3.1 DATA

The current study used the restricted data of the High School Longitudinal Study of 2009 (HSLS:09), a nationally representative dataset sponsored by the National Center for Education Statistics (NCES) (Ingels et al., 2011). HSLS:09 is a longitudinal study that surveyed students beginning in their ninth grade, with additional follow-ups scheduled as students transition to postsecondary education and the workforce. One of the goals of HSLS:09 was to help researchers and policy analysts investigate high school students' paths into and out of STEM curricula and occupations. HSLS:09 focuses on STEM education, making it ideal for examining the development of STEM career aspirations.

The HSLS:09 base-year data was collected in the 2009–2010 academic year with a sample of 9^{th} graders in public and private high schools in the United States. Students completed a mathematics assessment in person and a web-based survey with items on sociodemographic background, educational experiences and expectations, and their perceptions of the value of mathematics and science as a subject and occupation. Data for the first follow-up of HSLS:09 was collected in the spring of 2012 when most participants were in the 11th grade, and students completed a mathematics assessment and web-based survey again.

3.2 PARTICIPANTS

Base-year data were collected during the fall of the ninth grade. Students enrolled in the 9^{th} grade (not including foreign exchange students) in the sampled schools during the base-yeardata collection were considered eligible. Altogether 21,444 student

participants from 944 schools completed the student questionnaire in the base-year data collection in 2009, with a weighted response rate[4] of 85.7% (Ingels et al., 2015). The sample was representative of ninth-grade students in public and private schools in the United States in 2009, allowing for generalization to more than 4.2 million students at over 23,000 high schools. Data for the first follow-up was collected again from the same students in their 11th grade in 2012 (Ingels et al., 2015). Altogether 20,594 students completed the student questionnaire in the first follow-up with a weighted response rate of 82.0%. Students' demographic characteristics, such as sex, race/ethnicity, and socioeconomic status, were collected in both rounds of data collection (Ingels et al., 2015). The second follow-up data were collected from March 2016 through January 2017, about three years after most participants were expected to have graduated from high school (Duprey et al., 2018). By the time of the second follow-up, most students should have already entered 4-year postsecondary institutions, transitioned from community college settings to 4-year programs, or attained postsecondary certificates, 2-year degrees, and certifications granted by public institutions or for-profit schools. Altogether 25,123 participants remained eligible for the second follow-up, and 17,335 completed the survey, with a weighted response rate of 67.9% (Duprey et al., 2018).

The sample size used for the present study is smaller than the original sample size due to missing data on some of the variables and attrition in the follow-ups (see the Missing Data section for details about data cleaning). After data cleaning, 18,430 participants remained for the latent profile and latent transition analysis, 17,700 remained

[4] The weighted response rate is the rate of response calculated with exclusions made only for previously identified deceased and study ineligible sample members. Weighted response rate reflects the proportion of the eligible target population represented by sample respondents, and therefore serves as an indicator of data quality (Ingles et al., 2011).

for descriptive statistics that describe career aspiration stability, and 10,820 remained for descriptive statistics that show the consistency between career aspirations and major selection in college.

3.3 SAMPLE DESIGN

HSLS:09 used a stratified, two-stage random sample design. The primary sampling units were schools selected in the first stage and students randomly selected from the sampled schools in the second stage. Its target population of schools in the base year was regular public schools (including public charter schools) and private schools in the 50 states and the District of Columbia, where instruction is provided to students in both the 9th and 11th grades as of fall 2009. The student target population was all 9th-grade students who attended either public or private schools in the 50 states and the District of Columbia (Ingels et al., 2015).

In the first stage of sampling for the base-year survey of HSLS:09, stratified random sampling based on geographic region (Northeast, South, Midwest, West), school type (public, private-Catholic, private-other), and geographic location of the school (suburban, city, town, rural) resulted in the identification of 1,889 eligible schools in the 50 United States and the District of Columbia. In the end, 50.0% of these eligible schools chose to participate (the weighted school response rate was 55.5% (Holian & Kelly, 2020). In the second stage of sampling, 25,206 eligible students were randomly selected from school enrollment rosters (about 27 students in the 9th grade per school). Students were considered eligible as long as they were not foreign exchange students. All 25,206 base-year students who were study-eligible were included in the first follow-up sample, regardless of their enrollment and response status. Of these sample members, 25,184 remained eligible for the first follow-up. The student questionnaire included the items in

the base-year survey and added new items on various topics, such as grade progression, completion of admission tests, and college choice (Ingels et al., 2015). The second follow-up included 23,316 of the 23,401 sample members fielded and found eligible for the 2013 update (Duprey et al., 2018).

Unlike simple random sampling, where participants have an equal probability of being selected, participants are sometimes oversampled to ensure adequate measures in complex sample design. Oversampling creates an unequal probability of selection, which must be compensated for to make the results generalizable. Weights adjust for unequal probability of being selected and for non-response bias which can affect significance testing and lead to Type I errors (Ingles et al., 2004). Using survey weights enables making correct inferences about the finite population that is represented by the sample who took the survey.

The use of weights is critical to producing estimates that are representative of the HSLS:09 target student population. Although HSLS:09 was a national design to be representative of 9th-grade students across the United States in the 2009–2010 school year, in response to the National Science Foundation's request for representative estimates within some states, additional sample schools were added to the design to support the objectives of the revised study within ten states (Ingels et al., 2011). As a result, these states were overrepresented relative to other states. In addition, not all persons identified to provide contextual information for the sampled students agreed to participate in HSLS:09, creating non-response bias. Therefore, weights were created for analyzing HSLS:09 data to adjust for imbalances in the sampling and nonresponse (NCES, 2011). For instance, variables created for base year data were weighted by

W1STUDENT, and variables created for the first follow-up data were weighted by W2STUDENT. If the data were analyzed without utilizing weights, analyses would lead to estimated variances and confidence intervals that are too small, increasing the likelihood of Type I errors (Ingles et al., 2011).

Analytic weights were used in the present study combined with software that accounts for HSLS:09 complex survey design to produce estimates for the target population, with appropriate standard errors. When appropriately weighted, estimates from the HSLS:09 are generalizable to the U.S. population of ninth graders attending schools in the fall of 2009. To ensure that estimates are nationally representative, appropriate HSLS survey weights were employed in the LPA and LTA analysis. In the current study, LPA and LTA analysis were conducted using data from the base year and first follow-up; therefore, weight W2W1STU was used, which accommodates analysis that incorporates both base-year and first follow-up student questionnaires data (Ingles et al., 2011).

3.4 VARIABLES

Instrument design for HSLS:09 was guided by a conceptual model, and the questionnaire items reflect the constructs of EVT (Ingels et al., 2011). The model takes the student as the fundamental unit of analysis and seeks to identify factors that influence academic goal setting and education-related choices. It traces the many influences on students’ values and expectations that factor into their education-related decisions, such as math-science course taking, college, and occupations and careers (Ingles et al., 2011). The current study focuses on EVT motivational variables, differences between male and female students, STEM career aspirations, and STEM major choice.

Motivational Variables. All the motivational variables used in the current study were created by survey staff through principal component factor analysis (PCA), including mathematics/science self-efficacy, mathematics/science identity, mathematics/science interest, and mathematics/science utility[5]. These variables were represented with the same items in the base year and first follow-up student survey. Items used to create these variables were all on a four-point Likert scale (1 = Strongly agree, 2 = Agree, 3 = Disagree, 4 = Strongly Disagree). The survey staff calculated composite scores for these variables with PCA analysis. The composite scores were the factor scores standardized to a mean of 0 and standard deviation of 1 (Ingels et al., 2011). Only respondents who answered all items of a variable were assigned a composite score for that variable. Higher scores reflect higher motivation. There were items in the student survey about perceptions of cost in taking math and science courses. These items were on a Likert scale in the base year survey; however, they were on a nominal scale (Yes/No) in the first follow-up survey. Responses to a nominal scale could not be transformed to a composite variable that is suitable for latent profile analysis and latent transition analysis. Besides, the items were not worded in the same way in the first follow-up. Therefore, cost was not included in this study. The reliability of each scale was assessed using Cronbach's alpha.

Mathematics/Science self-efficacy. Two scale scores represented mathematics and science self-efficacy, respectively. The items used to construct these scales asked

[5] I recalculated the values of the 11th grade science utility variable using principal component analysis (PCA) because the variance of the variable seems too small to be correct ($\sigma^2 = .005$). The three items used to create science utility were reverse coded before conducting CFA. Factor scores from PCA were used to replace the original values for this variable.

students about their beliefs in their abilities to be successful in the current mathematics/science course. Four items were used to calculate a composite score for math/science self-efficacy. “You are confident that you can do an excellent job on tests in this course”. “You are certain that you can understand the most difficult material presented in the textbook used in this course”. “You are certain that you can master the skills being taught in this course”. “You are confident that you can do an excellent job on assignments in this course”. Higher values represent higher math/science self-efficacy. The mathematics and science self-efficacy scales had Cronbach’s alphas of .90 and .88, respectively (Ingels et al., 2011).

Mathematics/Science intrinsic value. Intrinsic value is operationalized as *mathematics*/science interest, representing participants’ interest in their math/science course, and higher values represent a greater interest in their math/science courses. Examples of items used to create this variable include “You are enjoying this class very much.” “You think this class is a waste of your time.” “You think this class is boring.” The math/science interest scale showed moderate reliability (α =.78 and α =.73, respectively) (Ingels et al., 2011).

Math/Science identity. Attainment value is operationalized as math/science identity, which is students’ belief about being a math/science person and being acknowledged by others as competent in mathematics. This scale measures how well the domain of math/science is compatible with the student’s identity. Participants were asked how well they agreed with statements such as “You see yourself as a math/science person” and “Others see you as a math/science person.” Those who tend to agree with these statements will have higher values for this variable. Mathematics attainment value

had a reliability of .84, and science attainment value had a reliability of .83 (Ingels et al., 2011).

Math/Science utility value. Utility value is operationalized as the usefulness of math/science courses for everyday life, college admission, and future career. The sample items include “What students learn in this course is useful for everyday life,” “What students learn in this course will be useful for college,” and “What students learn in this course will be useful for a future career.” Higher values represent perceptions of greater mathematics/science utility. Participants who tend to agree with these statements will have higher values. Scale reliability for math utility and science utility was .78 and .75, respectively (Ingels et al., 2011).

Auxiliary Variables. Two auxiliary variables were examined in the LPA and LTA analysis: sex and STEM career aspirations. Sex was examined as a covariate for latent profiles, and STEM career aspirations was examined as a distal outcome of latent profiles. The information on the sex variable was collected during the base year (2009) and the first follow-up (2012). Since there is some missing on the sex variable in the base year data but no missing on this variable in the first follow-up, sex in the first follow-up was used in the analysis that involves examining differences between male and female students.

STEM career aspirations in the base year and first follow-up were measured by students’ responses to the same question, “As things stand now, what is the job or occupation that you expect or plan to have at age 30?” Respondents were asked to indicate their expected occupations in the survey. All job titles were then coded by survey staff after data collection using the Bureau of Labor Statistics STEM classification based

on Standard Occupational Classification (SOC) codes[6] (Duprey et al., 2018). STEM career aspirations were coded as a categorical variable: 0 = “Not a STEM occupation”, 1 = “Life and Physical Science, Engineering, Mathematics, and Information Technology Occupations”, 2 = “Social Science Occupations”, 3 = “Architecture Occupations”, 4 = “Health Occupations”, 5= “Split across two STEM or STEM-related Sub-domains”, 6 = “Unspecified sub-domain”. Note that categories 1 to 6 were all STEM subcategories. When examining the stability of STEM career aspirations and consistency between STEM career aspirations and STEM major choice, categories 2, 3, 4, 5, and 6 were combined and re-coded as 1= “STEM”. Therefore, the career aspirations variable resulted in two categories, non-STEM and STEM. To examine how the 11th grade latent profile is related to 11th grade career aspirations in traditional STEM fields and health occupations, categories 1 and 4 were retained while categories 2 and 3 were dropped from the analysis because they don’t belong to either traditional STEM or health occupations.

STEM Major Choice. STEM major choice was represented by the first major or field of study for the postsecondary degree/certificate the respondent had declared or decided upon, as reported during the second follow-up interview in 2016. Data were collected from respondents who ever enrolled in a postsecondary degree or certificate program after high school. For students who had a double major for their degree/certificate, their “second major” does not impact the coding of this variable (X4RFDGMJSTEM). Students’ STEM major choice is a dichotomous variable where 1 indicates a STEM major and 0 indicates a non-STEM major. Majors within physical sciences and science technologies, engineering and engineering technologies, computer

[6] see http://www.bls.gov/soc/ATTACHMENT_B_STEM.pdf

and information sciences, mathematics and statistics, biological and biomedical sciences were coded as STEM.

3.5 MISSING DATA

Missing data occurs when a respondent does not answer a question either intentionally or unintentionally. Missing data appears in most of the variables used for the current study. There are only six missing values on the sex variable in base-year data, and there are no missing values on the sex variable in the first follow-up. Since the two rounds of data were collected from the same group of participants, the sex variable from the first follow-up – X2SEX[7] was used in all the analyses that examine differences based on sex.

Data cleaning was performed before running LPA and LTA analysis. To facilitate the analysis and interpretation of the LTA that uses data from both 9th grade and 11th grade, only participants who completed the survey at both time points were retained. As a result, 18,425 participants were retained. Next, data cleaning was performed on the STEM career aspirations variable. Only participants who provided data on this variable at both 9th grade and 11th grade were retained to model the stability or change of STEM career aspirations across the two time points. The cleaning resulted in 17,700 participants. Last, to model the consistency between 11th-grade career aspiration and major choice in college, only participants who completed the survey at both time points were retained. The cleaning resulted in 11,487 participants.

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[7] According to National Center for Educational Statistics, information on students' sex was obtained from the school and stored in his or her roster data; in addition, the student's sex was collected in the student interview and the parent interview. If there was a discrepancy across sources, the student's first name was reviewed to determine and store the correct value. Therefore, in the current study, students' assigned sex information was used to study differences between male and female students.

Most statistical software packages do not analyze records without complete information, which reduces the utility of the data. Mplus uses all available data to estimate the model parameters with FIML, which maximizes the utility of the data. FIML is considered one of the best approaches currently available to handle missing data (Acock, 2005; Enders, 2010; Molenberghs et al., 2014). It provides maximum likelihood estimation under MCAR (missing completely at random), MAR (missing at random), and NMAR (not missing at random) for continuous, categorical, or the combinations of these variable types (Little & Rubin, 2019; Muthén & Muthén, 1998-2015). In the current study, missing values on some of the motivational variables were estimated in Mplus using FIML before the LPA and LTA analysis process.

3.6 ANALYTIC APPROACH

General mixture modeling, specifically latent profile and latent transition analysis were used for this study. Latent profile models are a type of structural equation modeling, factor analysis, or random-effects modeling in which the latent variable is discrete rather than continuous (Skrondal & Rabe-Hesketh, 2004). Mixture modeling aims to recover hidden groups from observed data by making assumptions about what the hidden groups look like. It is possible to discover distributions within such groups and obtain the probability that each person belongs to one of the groups (Oberski, 2016). Mixture modeling often involves the investigation of what types of individuals belong to each class by relating latent classes to covariates, also known as auxiliary variables (Clark & Muthén, 2009).

LPA and LTA are chosen for the current study because they have advantages over variable-centered methods. Variable-centered analyses assume that all individuals within the sample belong to a single profile with no difference between latent subgroups. With a

variable-oriented statistical method, the modeling or description of several variables over individuals can be very challenging to translate into properties representing single individuals (Bergman & Magnusson, 1997). In the current study, a variable-centered approach could not accurately estimate whether a person with different levels of math and science expectancy and value beliefs would be interested in a STEM career. Advocates of person-oriented approaches argue that the complex and dynamic processes of individual development and functioning cannot be well understood by summarizing results from studies of individual variables investigated separately from other variables (Magnusson, 1998). A person-oriented approach such as LPA has potential advantages when dealing with multiple constructs. For instance, interpreting profiles of multiple variables is usually less challenging than interpreting patterns from interactions involving four or more variables in variable-oriented analyses. Besides, LPA identifies common combinations of variables that represent individuals in a given sample, so one does not have to interpret interactions that rarely occur (Perez, Wormington, et al., 2019). Finally, LPA can include demographics as covariates in the model for profile description (Magidson & Vermunt, 2002). With person-centered approaches like LPA, LTA, I can discern what math and science motivation profiles exist among high school students and whether these profiles are stable across high school years. By adding covariates to LPA and LTA models, I can find out whether there are differences between male and female students in motivation profiles and transition probabilities and how their differences in profile membership influence their career aspirations. LTA is appropriate when the latent group membership is hypothesized to change over time (Woo et al., 2018).

The LPA and LTA analyses were conducted using Mplus 8.6 with the robust maximum likelihood estimator. Parameter estimates were obtained by a procedure that repeatedly improves estimates and stopped when no further improvements could be obtained or until a maximum number of iterations was reached. The starting values were the values at which such repetitions were started. Increasing the number of iterations (cycles within each estimation) and setting more different starting values for each repetition leads to a greater likelihood that the global maximum of the log-likelihood function or the best possible solution is reached (Achterhof et al., 2019). I used 100 random sets of start values and a maximum of 20 iterations to estimate the LPA models and LTA models as recommended by Muthén and Muthén (1998-2015). The LTA models were estimated using the data from all respondents who completed both measurement points, focusing on the subset of participants who completed the survey at both time points.

Due to the stratified random sampling in the current study, there is clustering due to both primary(schools) and secondary sampling stages(students), which violates the assumption of independence. This violation would produce biased standard error estimates and increase the Type I error rate (McCoach & Adelson, 2010). To account for the effects of clustering due to the primary and secondary sampling stage, I used TYPE = COMPLEX MIXTURE analysis in Mplus, which adjusts the standard errors and fit statistics for clustering (Muthén & Muthén, 1998-2015). The CLUSTER option is used with VARIABLE to identify the variable containing clustering information, which is the variable PSU in the current study. The STRATIFICATION option is used with TYPE=COMPLEX to identify the variable containing information about the

subpopulations from which independent probability samples are drawn. In the present study, the variable is STRAT_ID.

Latent Profile Analysis (LPA). To examine high school students' math and science motivation profiles at the beginning of 9th grade and end of 11th grade, LPA models were estimated separately at each time point with the motivational variables as profile indicators (which were observed variables): math/science efficacy, math/science attainment value, math/science intrinsic value, and math/science utility value. I ran several models, starting from a one-profile model and adding a profile each time. I stopped adding more profiles when the BIC ceased to decrease or the size of latent profiles became too small (e.g., less than 5% of the whole sample). The means of profile indicator variables were freely estimated in all profiles, and the estimates of variances across the profiles were constrained to be equal. Each model was compared to the previous model(s) to decide the number of latent profiles in the data (Marsh et al., 2009; Masyn, 2013). The optimal model was determined based on model fit indices, classification quality, theoretical support, ease of interpretability, and meaningfulness of the profiles (DiStefano & Kamphaus, 2006; Muthén, 2003).

The following model fit indices were compared across the models to decide the optimal class/profile solution: 1) Akaike Information Criterion (AIC), 2) Bayesian Information Criterion (BIC), 3) the sample-size Adjusted BIC (SABIC), 4) entropy and 5) the adjusted Lo-Mendell-Rubin test (LMR) (Lo et al., 2001). Simulation studies indicate that these indices are particularly effective (e.g., Nylund et al., 2007; Peugh & Fan, 2013; Tein et al., 2013). AIC is a test of relative model fit and rewards parsimony. BIC is another parsimony index like AIC, which is particularly useful for evaluating LPA

models. SABIC is BIC with further sample size adjustment. Lower values in these three criteria suggest a better-fitting model. The BIC is particularly useful as it prefers parsimony in a model and has been shown to outperform other indices with continuous indicators (Morgan, 2015; Nylund et al., 2007). However, researchers have also pointed out that although lower values indicate better fit, lower is relative. Attention should also be paid to the magnitude of difference and the context when evaluating change between models. So far, there is no rule on what level of change in fit indices is considered "meaningful" (e.g., Masyn, 2013). The entropy provides a useful summary of classification accuracy (from 0–1), with higher values indicating more accuracy. However, it should not be used to determine the optimal number of profiles (Lubke & Muthén, 2007). An entropy level of 0.6 or above means sufficiently good class separation (Asparouhov & Muthén, 2014). The LMR test helps determine when adding an additional profile is not improving fit or model discrimination. A nonsignificant *p*-value in the LMR test suggests that the more parsimonious model is the representative and better fitting model (Ferguson et al., 2020).

In addition to evaluating fit, researchers need to review classification diagnostics (Masyn, 2013). The *average latent class posterior probability* is the average probability of the class model accurately predicting class membership for individuals (Muthén & Muthén, 2000). The interpretability and usefulness of the latent profiles and whether the solution is reasonable in relation to previous research and theory were also considered. Researchers claim that as in any model testing, the retained final model should have theoretical support, and the patterns or profiles uncovered should be interpretable (Marsh et al., 2004; Marsh et al., 2009; Masyn, 2013). Dependence on theory and prior research

is essential for evaluating the reasonableness of an LPA model and ensuring that the final model and its underlying profiles represent meaningful and interpretable classifications of individuals (Ferguson et al., 2020).

After the decision of optimal solution at each time point, I examined differences between male and female students in latent profile membership and how profile membership is related to career aspirations. Including auxiliary variables after the original model retention decision is supported by findings from simulation studies (Nylund-Gibson & Masyn, 2016). I ran two auxiliary models. The first model examines differences between male and female students in latent profiles of 9^{th} grade by adding sex as a covariate in the LPA model. The second model examines differences between male and female students in latent profiles of 11^{th} grade and how 11^{th} graders' profile membership is related to their career aspirations. Including a covariate and a distal outcome variable in the LPA model at the same time ensures that the effect of the latent profile variable on the distal outcome variable is controlled for by the covariate (Asparouhov & Muthén, 2021). In the second model, sex was specified to influence both the latent profile variable and the career aspirations variable.

The manual BCH method was used to estimate the two auxiliary models. BCH is a three-step approach. In the first step, the parameters of the LPA model are estimated without the covariate/distal outcome variable (which is already done when choosing the optimal solution). The second step of the estimation process is to save the BCH weights (computed based on the posterior probabilities of profile membership) for the latent profile variable. In the third step, the auxiliary model is estimated with the BCH weights (Asparouhov & Muthén, 2021). The BCH weights reflect the measurement error of the

latent profile variable (Bakk & Vermunt, 2014; Vermunt, 2010). BCH approach allows latent profile variables to be examined independently of the auxiliary variables, so adding the auxiliary variables into the model does not change profile membership (Asparouhov & Muthén, 2021; Vermunt, 2010).

Latent Transition Analysis (LTA). Latent transition analysis was performed to examine the stability of math and science motivation profiles from 9th grade to 11th grade and differences between male and female students in motivation profile stability. The following parameters were estimated in LTA: 1) proportion of individuals within each status at each time point (prevalence of latent statuses at each time point), 2) transition probabilities between the two time points (the probabilities of switching to another status given the current status), and 3) the parameter values of each status (means of the indicators). Transition probabilities refer to individual students' probability of changing from one profile to another between different time points, which reflect within-person stability.

If the same number and type of profiles are identified across both points of LPA, it is reasonable to explore the longitudinal measurement invariance before running LTA models (Nylund, 2007; Ryoo et al., 2018). Measurement invariance assumes equality of the measurement model parameters, specifically equality of conditional response means for LPA variables (Nylund, 2007). Measurement invariance assures that latent statuses can be interpreted in the same way across time, so it is easy to understand the transitions between latent classes/profiles (Meeus et al., 2011; Nylund, 2007). Measurement invariance testing is necessary for the current study because conditional response means

of the profile indicators were freely estimated in previous LPA models at the two time points, which may cause ambiguity when defining latent statuses in LTA.

Three levels of measurement invariance can be investigated: full measurement invariance, partial measurement invariance, and full measurement noninvariance. Full measurement invariance implies that the conditional response means are invariant (i.e., the same) across the different time points. The interpretation of the transition probabilities is straightforward with full invariance as the meanings of the profiles are the same across time. Partial measurement invariance means constraining some of the measurement parameters to be equal across time, while leaving the rest unconstrained. There are a number of possible invariance specifications. Full measurement noninvariance imposes no constraints on the measurement parameters across time (Nylund, 2007).

The invariance test was conducted by comparing the measurement invariance model (constraining the conditional response means of the profile indicators to be the equal at each time point) and the measurement non-variance (conditional response means were freely estimated at each time point) model with the likelihood ratio tests (LRT, based on loglikelihood values and scaling correction factors obtained with the MLR estimator). If the χ^2 test statistic of the LRT indicates no significant worsening of fit when equality constraints are imposed, then measurement invariance can be assumed. Full measurement invariance was first examined by constraining the number of latent statuses and item response means invariant across measurement occasions, which assumes there are the same number and type of profiles at each time point. Partial measurement invariance was then examined by imposing equality constraints for some measurement

parameters across time, while allowing others to vary freely (Nylund, 2007). Models with different measurement non-invariance specifications were fit and compared. For instance, one profile of the base year and first follow-up (9th grade and 11th grade) was freely estimated across time, while equality constraints were imposed on other profiles of these two time points (these profiles were invariant) if LPA results suggest such a trend. Another way to test partial measurement invariance is to focus on differential item functioning with respect to time. For instance, one item (or more) within a profile was noninvariant across time (e.g., math identity in Profile 1 of base year and first follow-up), while the rest of the parameters were held invariant. After testing measurement invariance, the most invariant model was retained for LTA without covariate to examine the prevalence of latent statuses at each time point and transition probabilities and define/name the latent statuses that are consistently identified over time (Ryoo et al., 2018). In the latent transition model, transition probabilities were freely estimated, which means students were allowed to transition from one status to any other status in the estimation. The entropy value should be above .60 for the best final LTA model (Asparouhov & Muthén, 2021). In the next step, the sex variable was added to the LTA model as a covariate to examine if male and female students differ in math and science motivation stability. Therefore, the LTA model included a measurement model for the latent profile variable at each time point and a structural model that related the latent profile variables to each other and the covariate (Muthén & Asparouhov, 2011).

Descriptive Statistics. Descriptive statistics was used to model career aspiration stability between 9th grade and 11th grade, and consistency between 11th-grade career aspiration and major choice in college. Percentages were calculated on students who had

the same career aspirations in 11^{th} grade as they had in 9^{th} grade, students who switched from having a non-STEM career aspiration in 9^{th} grade to having a STEM career aspiration in 11^{th} grade, and students who switched from having a STEM career aspiration to having a non-STEM career aspiration. Three percentages were calculated: percentage of students whose career aspirations in 11^{th} grade matched their first major in college, percentage of students who had non-STEM career aspirations in 11th grade but chose STEM as a first major, and percentage of students who had STEM career aspirations in 11th grade but chose a first major in a non-STEM field. Note that the first percentage included those who had STEM career aspirations in 11^{th} grade and chose STEM as their first major in college, and those who had non-STEM career aspirations in 11^{th} grade and chose non-STEM as their first major in college.

CHAPTER 4

RESULTS

4.1 LATENT PROFILE ANALYSIS

Descriptive Statistics of the Motivation Variables. Descriptive statistics of the latent profile indicators were run before running latent profile analysis. The means, standard deviations, maximum and minimum values of the eight motivation variables used for the base-year LPA analysis can be found in Table 4.1. Since the variables were standardized, all the means were around 0, and the standard deviations were around 1. The highest values were science identity (2.15) and math interest (2.08). The lowest values were math utility (-3.51) and science utility (-3.1).

Table 4.1 Descriptive Statistics of Motivation Variables at Base Year

Variable	Count	Mean	Min	Max	SD
Math Identity	18,250	.07	-1.73	1.76	1.00
Math Utility	16,310	-.01	-3.51	1.31	.99
Math Efficacy	16,290	.07	-2.92	1.62	.99
Math Interest	15,990	.06	-2.46	2.08	.99
Science Identity	18,210	.06	-1.57	2.15	1.00
Science Utility	15,030	.02	-3.10	1.69	.98
Science Efficacy	15,000	.06	-2.91	1.83	.99
Science Interest	14,740	.05	-2.59	2.03	.99

Note. SD = Standard Deviation. Detail may not sum to totals because of rounding.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09) Base Year

Correlations between the motivation variables in the base year can be found in Table 4.2. The correlation coefficients among the eight motivation variables ranged between .14 and .57. Some of the correlation coefficients were above the threshold of large correlation (>.50, according to Cohen's (1988) conventions)[8]. Large correlations were found between math interest and math identity (.54), math interest and math efficacy (.54), math efficacy and math identity (.57), science efficacy and science identity (.51), science utility and science interest (.51), science efficacy and science interest (.52). The correlation coefficients between math and science motivation variables were all below .50, ranging from .14 to .39. In other words, science efficacy and values were weakly or moderately correlated with math efficacy and values.

Table 4.2 Correlations of Motivation Variables at Base Year

	Math Identity	Math Utility	Math Efficacy	Math Interest	Science Identity	Science Utility	Science Efficacy	Science Interest
Math Identity	1							
Math Utility	.31	1						
Math Efficacy	**.57**	.36	1					
Math Interest	**.54**	.44	**.54**	1				
Science Identity	.28	.13	.19	.13	1			
Science Utility	.20	.43	.21	.24	.42	1		
Science Efficacy	.26	.19	.39	.17	**.51**	.40	1	
Science Interest	.14	.20	.14	.20	.48	**.51**	**.52**	1

Note. Correlation coefficients above .50 appear in boldface type.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09) Base Year.

Descriptive statistics for the eight motivation variables in the first follow-up can be found in Table 4.3. Means of motivation variables in the first follow-up were also

[8] According to Cohen (1988), a correlation coefficient of .10 represents a small or weak association; a correlation coefficient of .30 represents a moderate correlation; and a correlation coefficient of .50 or larger represents a large strong or correlation.

around 0, and the standard deviations were around 1. The lowest values were math utility (-3.94) and science utility (-3.21). The highest value was math interest (2.17).

Table 4.3 Descriptive Statistics of Motivational Variables at First Follow-up

Variables	Count	Mean	Min	Max	SD
Math Identity	18,130	.061	-1.54	1.82	1.02
Math Utility	18,080	.006	-3.94	1.21	1.00
Math Efficacy	17,910	.047	-2.50	1.73	1.00
Math Interest	15,320	.030	-1.89	2.17	1.01
Science Identity	18,050	.063	-1.74	1.86	1.01
Science Utility	17,980	.043	-3.21	1.50	1.00
Science Efficacy	17,720	.045	-2.47	1.64	.99
Science Interest	13,900	.043	-2.24	1.71	1.00

Note. SD = Standard Deviation. Detail may not sum to totals because of rounding.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09) First Follow-up.

Correlations between the motivation variables in the first follow-up can be found in Table 4.4. The correlation coefficients of the eight motivation variables range between .13 and .62. Similar to the findings in base year data, large correlation coefficients were found between math interest and math identity (.62), math interest and math efficacy (.58), math efficacy and math identity (.58), science efficacy and science identity (.53), science efficacy and science interest (.58). This time, two additional strong correlations were found between science utility and science identity (.54) and between science interest and science identity (.56). Like base year data, the correlation coefficients between math and science motivation variables were below .50 (ranging between .13 and .45), the threshold of large correlation.

Table 4.4 Correlations of Motivation Variables at First Follow-up

	Math Identity	Math Utility	Math Efficacy	Math Interest	Science Identity	Science Utility	Science Efficacy	Science Interest
Math Identity	1							
Math Utility	.43	1						
Math Efficacy	**.58**	.38	1					
Math Interest	**.62**	.44	**.58**	1				
Science Identity	.25	.17	.20	.13	1			
Science Utility	.22	.45	.23	.23	**.54**	1		
Science Efficacy	.18	.18	.31	.13	**.53**	.40	1	
Science Interest	.13	.19	.16	.21	**.56**	.46	**.58**	1

Note. Correlation coefficients above .50 appear in boldface type.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09) First Follow-up.

Latent Profile Analysis for the Base Year Data. Several latent profile solutions were estimated for the base year data with the eight motivation variables as profile indicators. The aim was to identify a parsimonious model with the best fit and the smallest number of meaningful groups. To do that, I tested models by increasing the number of profiles by one each time, starting with the one-profile model. I did not test beyond seven profiles as both the 6-profile and 7-profile solutions resulted in one cell containing less than 5% of the subjects. The fit and interpretability of each model were then compared with the more parsimonious model. Model fit indices can be found in Table 4.5. The 4-profile solution was considered the best. The decision was based on better model fit indices, classification probability, average latent class probabilities, interpretability, and theoretical support (Ferguson et al., 2020). First, the LMR test was significant for the 4-profile solution, which means it is better than the 3-profile solution. Although the 2-profile solution is better than the 1-profile solution, the BIC values continue to drop sharply with more profiles added. Researchers argued that the BIC may be the most reliable fit statistic (Nylund et al., 2007; Vermunt, 2002). Nylund-Gibson and

Choi (2018) introduced using an elbow plot of fit statistics to examine model fit[9]. The plot of BIC values revealed relatively large decreases until Model 4, as can be seen from the obvious elbow in Figure 4.1. The average latent class probabilities were above .80 in the 4-profile solution but below .80 from the 5-profile model. Besides, the profiles in the 4-profile solution make sense theoretically, as students' math and science motivation can be different (which was not reflected in the 3-profile solution).

Table 4.5 Fit Values for Different Profile Solutions of Base Year Data

Model	1-profile	2-profile	3-profile	4-profile	5-profile	6-profile	7-profile
AIC	364,690	348,420	343,047	338,047	336,109	334,171	332,551
BIC	364,815	348,615	343,313	338,383	336,516	334,648	333,099
SABIC	364,764	348,536	343,205	338,247	336,151	334,454	332,876
Entropy	NA	.66	.74	.67	.67	.68	.71
LMR *p*	NA	<.001	.079	<.001	.41	.49	.55
ALCP	1	.90	.87	.82	.79	.78	.79

Note. ALCP = average latent class probabilities; LMR p = p-value of the Lo-Mendell-Rubin test.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09) Base Year.

[9] AIC, BIC, and SAIC values of each solution were very close to BIC and overlapped in the plot, so only BIC values were plotted.

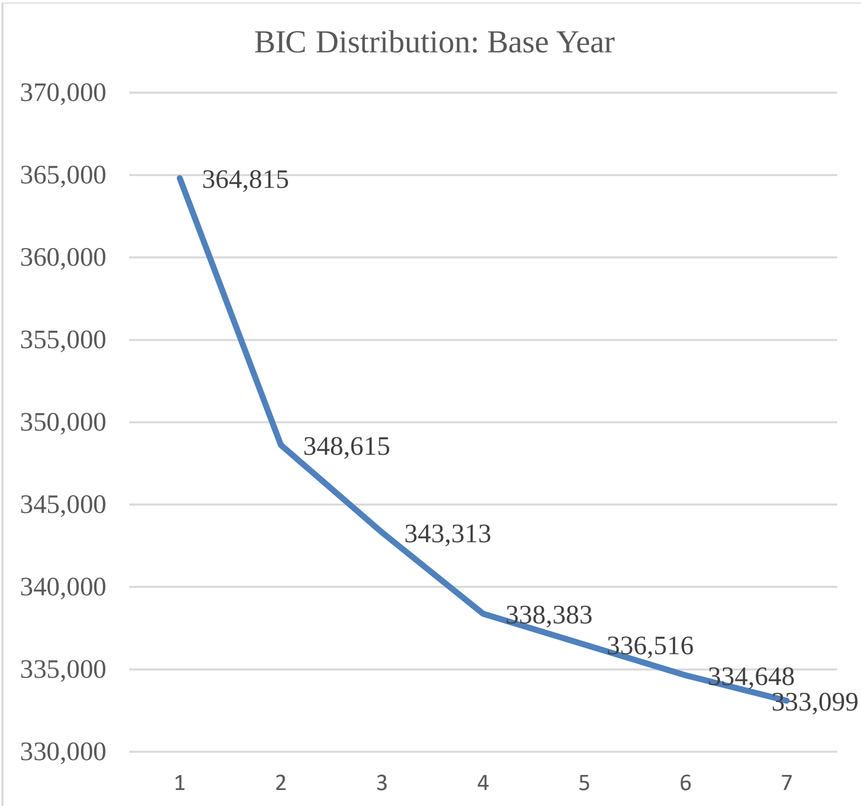

Figure 4.1 BIC Values of the Different Solutions for Base-year

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09) Base Year.

Figure 4.2 illustrates the profile allocation of the 4-profile model of the base year data. Table 4.6 summarizes profile sizes (including final class counts and proportions for the latent profiles based on estimated posterior probabilities), average profile membership probabilities for most likely latent profile membership, and conditional response means (in the form of Z scores) of the motivational variables in each profile. Based on the means of each motivation factor, the four profiles in the base year were named: 1) *Low All* (13.1%), 2) *Higher Science* (32.6%), 3) *Higher Math* (29.4%), and 4) *High All* (24.9%). In the *Low All* profile, students' math and science motivational beliefs were all very low, and some motivational beliefs were one standard deviation below the mean. In the *Higher Science* profile, students' math motivational beliefs were below average, while their

science motivational beliefs were above average. Their science motivational beliefs were remarkably higher than math motivational beliefs. In the *Higher Math* profile, students' math motivational beliefs were above average, while their science motivational beliefs were below average. Their math motivational beliefs were remarkably higher than their science motivational beliefs. In the *High All* profile, students' math and science motivational beliefs were all high.

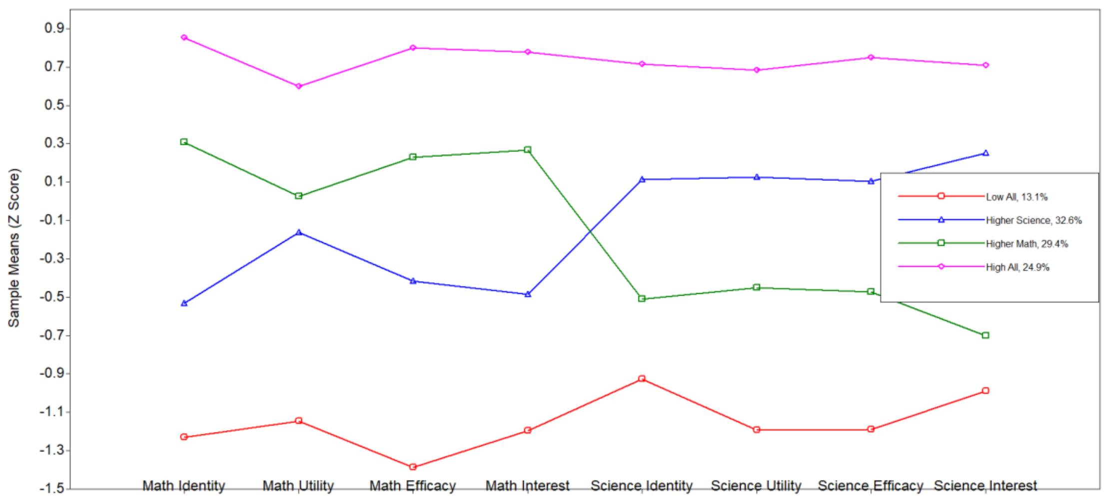

Figure 4.2 Profile Allocation of the 4-profile Solution (Base Year)

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09) Base Year.

Table 4.6 Profile Size, Average Probabilities of Most Likely Latent Profiles and Motivation Profile Conditional Response Means (the 4-profile solution for the base year)

Profile	N	%	AP MP	Math Identity	Math Utility	Math Efficacy	Math Interest	Science Identity	Science Utility	Science Efficacy	Science Interest
Low All	2,420	13.1%	.84	-1.13	-.94	-1.18	-1.02	-.80	-.91	-.98	-.81
Higher Science	4,590	24.9%	.79	-.42	-.21	-.35	-.40	.26	.19	.19	.34
Higher Math	6,000	32.6%	.78	.38	.05	.29	.38	-.47	-.40	-.43	-.60
High All	5,420	29.4%	.87	.90	.60	.85	.84	.81	.75	.80	.77

Note. APMP = Average profile membership probabilities. Detail may not sum to totals because of rounding.

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09) Base Year.

Latent Profile Analysis for the First Follow-up Data. Similarly, seven latent profile models were examined for the first follow-up data. The 4-profile solution was identified as the best fitting model based on model fit indices (see Table 4.7), theoretical support, interpretability, and classification quality. The AIC, BIC, and SAAIC continued to drop as more profiles were added, but the decrease was less sharp from the 5-profile model (See Figure 4.3). The LRT was significant for the 4-profile model but was insignificant for the 5-profile model. Besides, the entropy was better than the 3-profile solution. The above indices suggest that the 4-profile model was the best.

Table 4.7 Fit Values for Different Profile Solutions of First Follow-up Data

Model	1-profile	2-profile	3-profile	4-profile	5-profile	6-profile	7-profile
AIC	390,436	366,672	360,474	353,225	349,941	347,624	345,217
BIC	390,561	366,868	360,740	353,561	350,348	348,101	345,764
SABIC	390,510	366,788	360,632	353,425	350,183	347,907	345,542
Entropy	NA	.71	.69	.71	.76	.77	.76
LMR *p*	NA	<.001	.003	<.001	.40	.31	.24
ALCP	1	.91	.85	.84	.85	.84	.83

Note. ALCP = Average Latent Class Probabilities. LMR *p* = *p*-value of the Lo-Mendell-Rubin test.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09) First Follow-up.

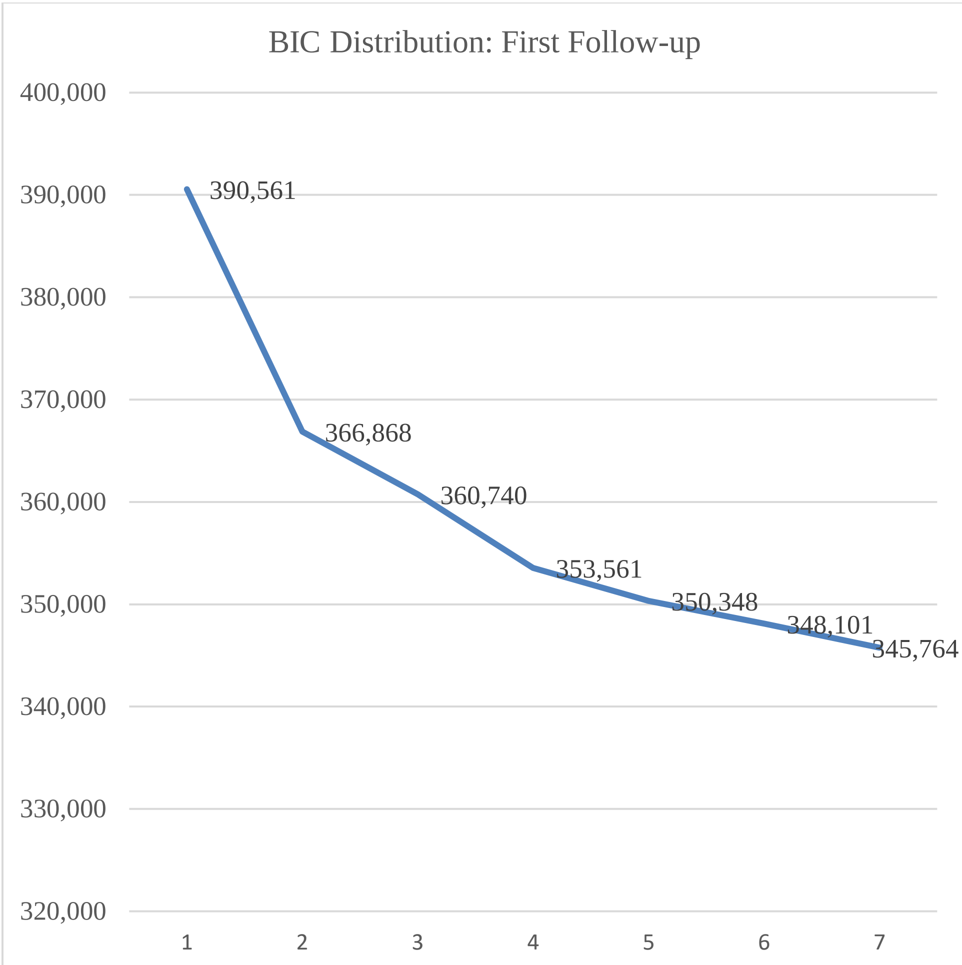

Figure 4.3 BIC Values of the Different Solutions for the First Follow-up

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09) 1st Follow-up

Figure 4.4 illustrates the profile allocation of the 4-profile model for first the follow-up. Table 4.8 summarizes profile sizes (including final class counts and proportions for the latent profiles based on estimated posterior probabilities), average profile membership probabilities for most likely latent profile membership, and means of the motivational variables in each profile. Based on the distribution of the profile indicator means, the four profiles were named 1) *Low All* (20.1%); 2) *Higher Science* (32.3%); 3) *Higher Math* (29.1%); 4) *High All* (18.5%). The profile names were the same with those in the base year, because they share similar characteristics. In the *Low All*

profile, students' math and science motivational beliefs were all very low. In the *Higher Science* profile, students' math motivational beliefs were below average, while their science motivational beliefs were above average. In the *Higher Math* profile, students' math motivational beliefs were above average, while their science motivational beliefs were below average. In the *High All* profile, students' math and science motivational beliefs were all high.

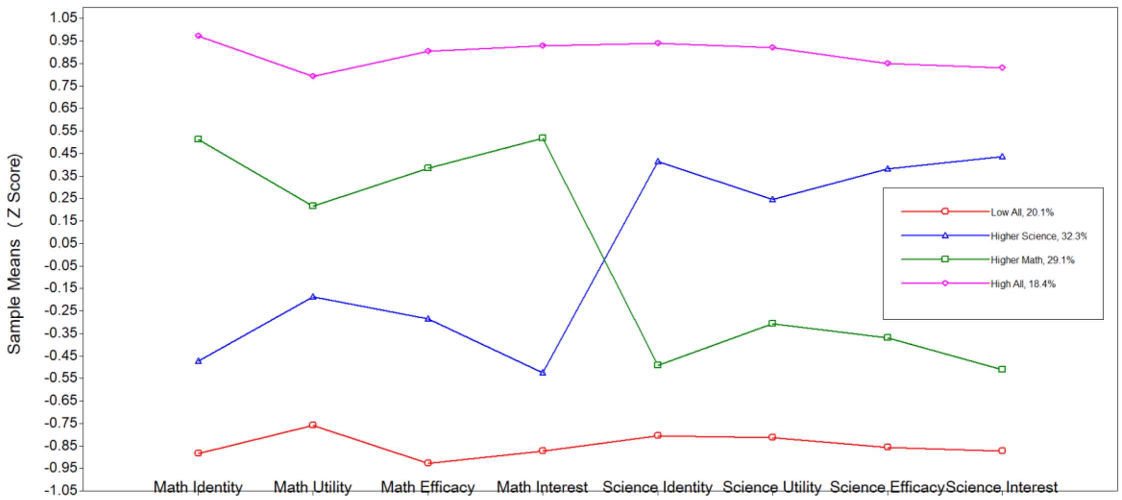

Figure 4.4 Profile Allocation for the 4-profile Solution (first follow-up)

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09) First Follow-up.

Table 4.8 Profile Size, Average Probabilities of Most Likely Latent Profiles, and Motivation Profile Conditional Response Means (the 4-profile solution for the first follow-up)

Profiles	N	%	APMP	Math Identity	Math Utility	Math Efficacy	Math Interest	Science Identity	Science Utility	Science Efficacy	Science Interest
Low All	3,710	20.1%	.85	-.89	-.76	-.93	-.87	-.80	-.81	-.86	-.87
Higher Science	3,400	32.3%	.82	-.47	-.19	-.29	-.53	.41	.25	.38	.44
Higher Math	5,370	29.1%	.82	.51	.21	.39	.52	-.49	-.31	-.37	-.51
High All	5,950	18.5%	.88	.97	.79	.90	.93	.94	.92	.85	.83

Note. APMP = Average profile membership probabilities. Detail may not sum to totals because of rounding.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09) First Follow-up.

Differences Between Male and Female Students in Latent Profiles. Sex was added to the 4-profile model at each time point as a covariate, using the BCH approach. Table 4.9 presents the logistic regression odds ratios, 95% confidence intervals and *p*-value of the odds ratios for the LPA analysis of each time point, with the *Low All* profile as the reference group. As such, three covariate comparisons were made: (1) the likelihood of being in the *Higher Science* profile compared to the *Low All* profile, (2) the likelihood of being in the *Higher Math* profile compared to the *Low All* profile, and (3) the likelihood of being in the *Higher Math & Higher Science* compared to the *Low All* profile.

Table 4.9 Logistic Regression Results for the Sex Covariate

Model	OR	95% CI	*p*
LPA1			
Higher Science	.73*	.59, .89	<.001
Higher Math	1.02	.84, 1.25	.84
High All	.93	.76, 1.15	.49
LPA2			
Higher Science	.84*	.72, .98	.017
Higher Math	.78*	.66, .92	.001
High All	.56*	.47, .67	<.001

Note. OR = Odds Ratio. * $p < .05$. The parameters were estimated with *Low All* as the reference group at each time point.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09) Base Year and First Follow-up.

For the base year, the odds of being in the *Higher Science* profile relative to the *Low All* profile is 27% lower (OR = .73, 95% CI [.11, 41], $p < .001$) for female students than male students. Or female students have .73 times the odds of male students being in the *Higher Science* profile. The odds of being in the *Higher Math* and *High All* profile relative to *Low All* profile were not statistically different between male and female students. In the first follow-up, the odds of being in all the other three profiles relative to

the *Low All* profile were lower for female students than male students. The odds of being in the *Higher Science* profile was 16% lower (OR = .84, 95% CI [.72, .98], p = .017), the odds of being in the *Higher Math* profile was 22% lower (OR = .78, 95% CI [.66, .92], p = .001), and the odds of being in the *High All* profile was 44% lower (OR = .56, CI [.47, .67], $p < .001$) for female students than male students. Female students had consistently lower odds of being in the *Higher Science* profile across the two time points. The difference is that female students were less likely to be in the *Higher Math* profile and the *High All* profile than male students in the first follow-up, while there was no significant difference between them in the base year.

4.2 LATENT TRANSITION ANALYSIS

Since the 4-profile solution was considered optimal in both the base year and the first follow-up, and the characteristics of the four profiles appeared consistent across time, the four-status model was chosen to do the latent transition analysis. Before running LTA, cross-sectional results can first be used to describe the changes. A cross-tabulation of profile membership at each time point provides a preliminary description of the type of movement in the sample (See Table 4.10). There are a few things to note when comparing the profile sizes presented in Table 4.10. First, there was a large increase in the *Low All* profile, from 13.1% to 20.1%. Second, there was a noticeable decrease in the *High All* profile, from 24.9% to 18.4%. The changes in profile sizes of the *Higher Science* and *Higher Math* profile were small. The changes in profile sizes suggest a trend of decrease in math and science motivation as students moved up the grades in high school. However, this assumption was based only on the cross-sectional analysis when the latent profile means were freely estimated. To describe the type of movement among the four motivation profiles over time with latent transition analysis, it is necessary to first determine whether the latent

profiles across time are the same or at least similar. Formal measurement invariance testing was used to verify if the selected measurement model was invariant across time.

Table 4.10 Percentage of Students in Each Motivation Profile in Grade 9 and Grade 11

Profiles	Grade 9	Grade 11
Low All	13.1%	20.1%
Higher Science	32.6%	32.3%
Higher Math	29.4%	29.1%
High All	24.9%	18.4%

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09) Base Year and First Follow-up.

Measurement Invariance Testing. The full measurement invariance test results indicated a significant difference in fit between the measurement non-invariance and the measurement-invariance model. The model with complete measurement non-invariance had a better model fit than the full measurement invariance model. A series of partial measurement invariance models were fit based on the results of cross-sectional LPAs and compared to the full invariance model. The following partial invariance models were considered: a model that allowed all the item parameters to be noninvariant for the *Low All* profile, while the other three profiles were held invariant (because the biggest profile indicator mean differences occur in this profile, with the mean differences in 6 out of 8 indicators greater than .30); a model that allowed all the item parameters to be noninvariant for the *Low All* and *Higher Math* profile, while the other two profiles were held invariant; a model that allowed math motivation variables to be noninvariant, while science motivation variables were held invariant; a model that allowed identity, efficacy, and interest to be non-invariant, while utility value was held invariant; and several other

models that allowed different combinations of items within each profile to vary across time. Although the results indicated statistical improvement in fit for all the partial invariance models compared to the full invariance model, no model stood out as a better fitting model. In other words, there was not one partial measurement invariance model that appeared the most reasonable among those considered. Therefore, full measurement noninvariance was assumed (not constraining latent status indicator means to be the same) because of not finding a partial measurement invariance model that made statistical and practical sense. Even though measurement invariance cannot be assumed, it still makes sense to run the latent transition analysis because the plots of the profiles at the two time points were remarkably similar across time, and the differences in conditional response means across time were small. It is still easy to interpret the transitions between the two time points, as the meanings of the latent profiles were quite similar.

Latent Transition Analysis without Covariates. The LTA model without covariates had an entropy of 0.74, which is acceptable. Final profile counts and proportions for each latent profile variable were based on estimated posterior probabilities. Based on the LTA results, the latent statuses were named: Status 1 = *Low All;* Status 2 = *Higher Science*, Status 3 = *Higher Math*, Status 4 = *High All*. The means of the status indicators can be found in Table 4.11. There were some differences between status indicator means at the two time points, but the differences were mostly small. Some small shifts in profile size were found. For instance, the size of the *Low All* profile in 9^{th} grade was 13.1% in LPA, but it changed to 13.2% in LTA. The size of the *High All* profile in 9^{th} grade was 24.9% in LPA, but it changed to 23.8% in LTA.

Table 4.11 Latent Status Indicator Means (base year/first follow-up)

Status Indicator	Low All	Higher Science	Higher Math	High All
Math Identity	-1.12/-.90	-.56/-.52	.39/.52	.90/1.01
Math Utility	-.95/-.74	-.13/-.16	.08/.19	.60/.77
Math Efficacy	-1.13/-.92	-.40/-.27	.26/.35	.81/.90
Math Interest	-.1.01/-.86	-.48/-.49	.31/.45	.78/.91
Science Identity	-.90/-.78	.21/.45	-.46/-.48	.83/.93
Science Utility	-.1.08/-.78	.19/.29	-.33/-.32	.71/.89
Science Efficacy	-1.07/.-82	.16/.40	-.35/-.35	.79/.83
Science Interest	-.94/-.84	.31/.47	-.53/-.48	.77/.79

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09) Base Year and First Follow-up.

The transition matrix (see Table 4.12) describes the probability of staying in the same latent status and transitioning to a different status in 11th grade conditional on 9th-grade latent status. The transition matrix shows that most students were more likely to stay in the same status across time than transition to another status. The probability of staying in the same status ranged between 56.4% and 66.8%. The *High All* status showed a lower degree of stability (56.4%) than the other three statuses (65.8%, 62.6%, and 66.8%, respectively). The most likely transitions were from *Higher Science* to *Low All* (23.1%), from *High All* to *Higher Science* (21.7%) and *Higher Math* (20.5%), and from *Low All* to *Higher Science* (19.1%). The probability of transitioning from *Low All* to the other three statuses (from lower to higher motivation) was 34.2% in total; and from *High All* to the other three statuses (from higher to lower motivation) was 43.6% in total. The probability of transitioning from *Higher Science* and *Higher Math* to *High All* (from lower to higher motivation) was 15.4% in total. The probability of transitioning from these two statuses to *Low All* was 37.6% in total (from higher to lower motivation).

Table 4.12 Latent Status Prevalence and Estimated Latent Transition Probabilities

Latent status	Grade 9	Transition Matrix Low All	Higher Science	Higher Math	High All	Grade 11
Low All	.132	**.658**	.191	.130	.021	.209
Higher Science	.316	.231	**.626**	.081	.062	.305
Higher Math	.313	.145	.094	**.668**	.092	.301
High All	.238	.013	.217	.205	**.564**	.186

Note. The stability of each latent status appears in boldface type.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09) Base Year and First Follow-up.

Transition Probability by Sex. An LTA model with a covariate of sex was estimated to examine differences between male and female students on transition probabilities. In this model, profile membership at first follow-up (T2) was predicted by profile membership at base year (T1), and by sex while controlling for previous latent status. Table 4.13 and Table 4.14 show the estimated latent transition probabilities for male and female students separately. The results indicate that in general, both male and female students' motivation statuses were still relatively stable. Male students' probabilities of staying in the same status ranged between 59.7% and 68.1%, and female students' probabilities of staying in the same status ranged between 51% and 69%.

Table 4.13 Estimated Latent Transition Probabilities for Male Students (*N*=9,240)

Status	Low All	Higher Science	Higher Math	High All
Low All	**.646**	.188	.140	.025
Higher Science	.223	**.616**	.088	.074
Higher Math	.132	.085	**.681**	.103
High All	.012	.191	.200	**.597**

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09) Base Year and First Follow-up.

Table 4.14 Estimated Latent Transition Probabilities for Female Students (N=9,190)

Status	Low All	Higher Science	Higher Math	High All
Low All	**.690**	.182	.112	.016
Higher Science	.251	**.627**	.074	.048
Higher Math	.169	.098	**.655**	.077
High All	.017	.253	.219	**.510**

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09) Base Year and First Follow-up.

A series of Wald tests were then used to compare if differences between male and female students in transition probabilities were statistically significant. A Bonferroni correction of .0031 was used since 16 comparisons were made. Wald tests results revealed four transition paths with significant differences (see Table 4.15). Male students were more likely to stay in the *High All* status than female students ($p < .001$). Male students were more likely to transition from the *Higher Science* status to the *High All* status ($p < .001$), and from the *Higher Math* status to the *High All* status ($p = .003$). Female students were more likely to transition from the *High All* status to the *Higher Science* status ($p < .001$).

Table 4.15 Transition Probabilities by Sex

	χ^2	df	*p*
Low All -> Low All	6.69	1	.010
Low All -> Higher Science	.275	1	.60
Low All -> Higher Math	6.49	1	.010
Low All -> High All	7.49	1	.006
Higher Science -> Low All	3.62	1	.057
Higher Science -> Higher Science	.38	1	.537
Higher Science -> Higher Math	3.76	1	.052
Higher Science -> High All	16.99*	1	<.001
Higher Math -> Low All	7.56	1	.006
Higher Math -> Higher Science	3.81	1	.05
Higher Math -> Higher Math	1.79	1	181
Higher Math -> High All	8.91*	1	.003
High All -> Low All	7.56	1	.006
High All -> Higher Science	12.64*	1	<.001
High All -> Higher Math	1.53	1	.216
High All -> High All	11.71*	1	<.001

Note. χ^2 is the Chi-square statistic value. * denotes significance at Bonferroni-adjusted *p*-value of .0031.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09) Base Year and First Follow-up.

4.3 ASSOCIATION BETWEEN LATENT PROFILE MEMBERSHIP AND STEM CAREER ASPIRATIONS

To examine the association between motivation profile membership and career aspirations and the differences between male and female students in career aspirations, an auxiliary LPA model was run with career aspirations as the outcome variable, latent profile as the predictor variable, and sex as the covariate. To more closely examine the relationship between motivation profile membership and career aspirations in traditional STEM fields and health occupations, the career aspiration variable was dummy coded as traditional STEM and health occupations with non-STEM as the reference group (See Table 4.16 for the percentage of each category). Traditional STEM and health occupations were then separately examined as the outcome variables.

Table 4.16 Percentage of Different Career Aspirations in the First Follow-up

Non-STEM	Traditional STEM	Health Occupations	Other[10]	Total
11,590(62.9%)	1,710(9.3%)	4,230(23.0%)	890(4.8%)	18,430(100.0%)

Note. Data for this variable is from the sample of students for LPA2 analysis. The category "other" includes those coded as "Split across 2 sub-domains", "Unspecified sub-domain", "Uncodeable" and "Missing". Detail may not sum to totals because of rounding.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09) First Follow-up.

BCH approach was used to examine the relationships. Pair-wise comparison tests were used to compare differences in career aspirations across profiles (See Table 4.17). Given there were six pairwise comparisons, a Bonferroni-corrected alpha of .008 was used. The results indicated significant differences between the *Low All* profile and each of the other three profiles in aspirations for traditional STEM careers. Students in this profile were less likely to aspire to a traditional STEM career at the age of 30 than students in all the other three profiles (p<.001). Students in the *High All* profile were more likely to aspire for a STEM career than students in the other three profiles (p<.001). There were no significant differences between students in the *Higher Science* profile and the *Higher Math* profile in traditional STEM career aspirations (p=.034).

Significant differences existed between students in any two profiles regarding aspirations for health occupations. Students in the *Low All* profile were less likely to aspire for health occupations than students in any other profiles (p<.001). Students in the *High All* profile were more likely to aspire for health occupations than those in any other profiles (p<.001). Students in the *Higher Science* profile were more likely to aspire for health occupations than students in the *Higher Math* profile (p<.001).

[10] This category was coded as missing in the LPA analysis with career aspirations as the outcome variable.

Table 4.17 Differences in Proportion of Students Aspiring for Traditional STEM and Health Occupations between Profiles

	Difference	S.E.	P-Value
Traditional STEM			
Low All vs Higher Science	-.06*	.011	<.001
Low All vs Higher Math	-.09*	.012	<.001
Low All vs High All	-.30*	.013	<.001
Higher Science vs Higher Math	-.03	.013	.034
Higher Science vs High All	-.23*	.015	<.001
Higher Math vs High All	-.21*	.016	<.001
Health Occupations			
Low All vs Higher Science	-.14*	.013	<.001
Low All vs Higher Math	-.04*	.011	<.001
Low All vs High All	-.20*	.013	<.001
Higher Science vs Higher Math	.10*	.013	<.001
Higher Science vs High All	-.06*	.015	<.001
Higher Math vs High All	-.16*	.014	<.001

Note. * denotes significance at Bonferroni-adjusted *p*-value of .008.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09) First Follow-up.

The logistic regression results (see Table 4.18) indicate no statistically significant differences between male and female students in their odds of being interested in traditional STEM careers among students in the *Low All* profile and the *Higher Science* profile relative to non-STEM careers. Within the *Higher Math* profile, the odds of female students to aspire for traditional STEM careers were 7% lower than male students (OR = .93, 95% CI [.91, .95], $p<.001$). Or female students have .93 times the odds of male students aspiring for a traditional STEM career. Within the *High All* profile, the odds of female students to aspire for traditional STEM careers were 15% lower (OR = .85, 95% CI [.82, .87], $p<.001$) than male students. Female students in each profile had higher odds to aspire for health occupations than male students relative to non-STEM careers. Within

the *Low All* profile, the odds of female students to aspire for health occupations were 14% higher (OR = 1.14, 95% CI [1.11, 1.12], p <.001) than male students. Within the *Higher Science* profile, the odds of female students to aspire for health occupations were 27% higher (OR = 1.27, 95% CI [1.23, 1.31], p <.001) than male students. Within the *Higher Math* profile, the odds of female students to aspire for health occupations were 22% higher (OR = 1.22, 95% CI [1.19, 1.26], p <.001) than male students. Within the *High All* profile, the odds of female students to aspire for health occupations were 37% higher (OR = 1.37, 95% CI [1.32, 1.42], p <.001) than male students.

Table 4.18 Differences between Male and Female Students in Aspirations for Traditional STEM and Health Occupations

	OR	95% CI	*p*
Traditional STEM			
Low All	1.01	1.00, 1.03	.162
Higher Science	1.01	.99, 1.04	.207
Higher Math	.93*	.91, .95	<.001
High All	.85*	.82, .87	<.001
Health Occupations			
Low All	1.14*	1.11, 1.12	<.001
Higher Science	1.27*	1.23, 1.31	<.001
Higher Math	1.22*	1.19, 1.26	<.001
High All	1.37*	1.32, 1.42	<.001

Note. * p < .05. The parameters were estimated with "non-STEM" as the reference group.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09) First Follow-up.

4.4 CAREER ASPIRATION STABILITY, CAREER ASPIRATION AND COLLEGE MAJOR CHOICE

The distribution of career aspirations at age 30 was similar in both base year (2009) and first follow-up (2012), but there were changes within career categories. Table 4.19 shows the frequency of students' career aspirations in STEM and non-STEM fields

at each time point. A few more students (about 2.7%) aspired for a STEM career in the first follow-up than the base year.

Table 4.19 Frequency of Different Career Aspirations among High School Students in Base Year and First Follow-up

	Non-STEM	STEM	Total
Base Year	11,780(66.5%)	5,920(33.5%)	17,700(100%)
First Follow-up	11,290(63.8%)	6,410(36.2%)	17,700(100%)

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09) Base Year and First Follow-up.

Table 4.20 shows that over 70% of the students held the same career aspirations across the two time points, but 13.3% of students who reported intentions for a STEM (including traditional STEM and health occupations) career at age 30 in 2009 reported intentions for an occupation in a non-STEM field in 11th grade. In the meantime, 16% of students who reported intentions for a non-STEM career in 9th grade reported intentions for a STEM career in 2012.

Table 4.20 Career Aspiration Stability from Base Year to First Follow-up

Same	Non-STEM to STEM	STEM to Non-STEM	Total
12,510(70.7%)	2,840(16%)	2,350(13.3%)	17,700(100%)

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09) Base Year and First Follow-up.

Although it is only logical to choose a STEM major in college if a student wants to have a career in a STEM field, it is not always the case due to various reasons. In the current study, students in 11th grade who had STEM career aspirations might not choose a STEM major in college. Of the 10,820 students who reported both career aspirations in 11th grade and major selections in college, 62.6% of them chose a college major that was consistent with their career aspirations in 11th grade. About 9.5% of them selected a STEM major in college even though they did not aspire to have a STEM career when

they were in 11th grade, and 27.9% of them who aspired to a STEM career in 11th grade ended up selecting a non-STEM major in college (see Table 4.21).

Table 4.21 Consistency of Career Aspirations in High School and College Major Selection

Same	Non-STEM to STEM	STEM to Non-STEM	Total
6,770(62.6%)	1,030(9.5%)	3,020(27.9%)	10,820(100%)

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS:09) First Follow-up and Second Follow-up.

CHAPTER 5

DISCUSSION

Using Expectancy-Value Theory, this longitudinal study examined high school students' math and science motivation profiles (with math and science identity, utility, efficacy, and interest as profile indicators) at 9th and 11th grade, the stability of their motivation profiles, and how 11th-grade motivation profile is related to STEM career aspirations. Differences between male and female students in motivation profiles, profile transition probabilities and STEM career aspirations were examined along the way. The study also examined the stability of career aspirations in high school, and the consistency of 11th-grade career aspirations and first major in college. Specifically, latent profile analysis was used to classify the sampled high school students into different groups according to their shared pattern of math and science motivational beliefs. Latent transition analysis was used to examine the stability and transition probability of students' motivation profiles from the beginning of 9th grade to the end of 11th grade. An auxiliary LPA model was used to examine how 11th grade math and science motivation profile membership relates to STEM career aspirations. Results from the analyses yielded several main findings. First, similar motivation profiles were identified at the two time points. In some of the profiles, students' math motivation and science motivation were on remarkably different levels. Differences between male and female students were more evident in 11th grade than in 9th grade. Second, most students' motivation profile was stable between 9th and 11th grade, but a considerable number of them (33.2% - 43.6%)

switched to a different profile. There were both adaptive and maladaptive changes. Male students were more likely to move to profiles with higher math and/or science motivation, but female students were more likely to move to profiles with lower math and/or science motivation. Third, in general, students in latent profiles characterized by higher math and science motivation were more likely to be interested in traditional STEM and health occupations. Students in the *Higher Science* profile were more likely to be interested in health occupations than those in the *Higher Math* profile, but they did not differ in aspirations for traditional STEM careers. Female students in each motivation profile were more likely to be interested in health occupations than male students, while female students in the *Higher Math* profile and the *High All* profile were less likely to be interested in traditional STEM careers than male students in these two profiles. Fourth, students' career aspirations remained relatively stable from 9th grade to 11th grade, and most students who had STEM career aspirations in 11th grade picked a STEM major in college. The rates of switching from STEM to non-STEM career aspirations and otherwise were similar. However, the rate of students having a STEM career aspiration in high school but choosing a non-STEM major in college is much higher than that of students having a non-STEM career aspiration in high school but choosing a STEM major in college. This chapter discusses these findings one by one and provides implications of the results, limitations, and suggestions for future research.

5.1 STUDENTS' MOTIVATION PROFILES IN 9TH AND 11TH GRADE

One of the research aims of the current study was to identify motivation profiles in high school students when they were in 9th grade and 11th grade, using constructs from Expectancy Value Theory. The study found four motivation profiles at each time point in

the sampled students who were representative of all high school students in the U.S. in 2009 and 2012. The four-profile solutions were very much alike.

One interesting finding is that while two of the four profiles at each time point were characterized by similar levels of math and science motivation (the *Low All* profile and the *High All* profile), the other two profiles were characterized by distinctly different levels of math and science motivation (the *Higher Science* profile and the *Higher Math* profile). The combinations of different math and science motivation levels within a profile were directly evidenced by the low correlation between math and science motivational beliefs. The correlation matrix in Table 4.2 and Table 4.4 showed that the correlations between the math motivational beliefs were mostly large, so were the correlations between the science motivational beliefs. However, the correlations between math and science motivational beliefs were mostly low and sometimes moderate. Previous research also found low correlations between math and science expectancies and interests (e.g., Else-Quest et al., 2013; Li et al., 2002). Therefore, using a composite score that averages math and science motivational beliefs is inappropriate because one can have high math motivation and low science motivation at the same time, and vice versa. Simply averaging math and science motivation would conceal the difference. Furthermore, ignoring this difference could lead to the failure of discovering how the difference might lead to different outcomes within individuals. Researchers have called on using adolescents' motivational beliefs in more than one domain to understand their STEM pathways development (Wang & Degol, 2017). Since math and science courses are the foundations of most STEM fields, it is necessary to simultaneously examine math and science motivation as the indicators of motivation profiles. The person-oriented

approach applied in this study is an ideal method for studying math and science motivations simultaneously.

Besides the overall response pattern, it is also necessary to investigate the response pattern within a profile. The conditional response means suggest variation in agreement on profile indicators within each profile. For instance, in the *High All* and the *Higher Math* profile of 9th grade, math utility was clearly lower than the other math motivational beliefs. In contrast, math utility was higher than other math motivational beliefs in the *Low All* and *Higher Science* profiles. A similar pattern was also found in the latent profiles of 11th grade. This might be because utility value is not necessarily highly correlated with expectancies, or with intrinsic and attainment value even though there is often high correlation between attainment value and intrinsic value (e.g., Hulleman et al., 2008; Trautwein et al., 2012). In other words, recognizing the usefulness of a subject does not mean one is interested in it or good at it. These findings suggest that there is still a need to study the value components separately. However, it must be noted that even though there is variation in their expectancy and value levels, one still needs to have all of them on a relatively high level to be more likely to choose STEM careers. This has been shown by previous research findings with person-centered approaches (e.g., Aschbacher et al., 2014; Lazarides et al., 2020) and variable-centered approaches (e.g., Guo, Parker et al., 2015; Trautwein et al., 2012).

Differences between male and female students were found in motivation profiles, with female students less likely to be in profiles with higher motivation. Similar findings were documented in studies that examined students' math and/or science motivation with latent profile analysis (Chow et al., 2012; Dang & Nylund-Gibson; 2017; Fong et al.,

2021). The differences were more obvious in 11th grade than in 9th grade. In 9th grade, female students were only less likely to be in the *Higher Science* profile than male students. They did not differ from male students in their likelihood of being in the *Higher Math* profile and the *High All* profile relative to the *Low All* profile. But in 11th grade, female students were less likely to be in all the other three profiles relative to the *Low All* profile, including the *Higher Math* and the *High All* profile. This change suggests a decrease in female students' motivational beliefs (which can also be seen in the LTA results) through high school years, especially in math motivation. Overall, findings from the LPA analysis suggest that there is high heterogeneity in high school students' math and science motivation which needs to be attended to in classroom instructions.

5.2 MOTIVATION PROFILE STABILITY

In 9th grade, students were beginning to experience high school math and science, and by 11th grade, they had already studied high school math and science for over two years and reached a stage where they needed to finalize plans for college. Their experience with math and science courses over this time might have impacted their math and science motivation and then influenced their STEM outcomes, such as career aspirations and preference of college major. The current study examined the stability and change of math and science motivation profiles (or latent status in LTA analysis) from 9th grade to 11th grade. Two kinds of motivation stability were examined: within-sample stability and within-person stability. Within-sample stability examines whether there are different latent classes present in the data or the stability of the profile structure within a sample. Since in both base year and the first follow-up, the four-profile solution was considered the best, and the profile structure was quite similar, within-sample stability roughly holds.

Since the measurement invariance test did not find the conditional response means of the latent status indicators to be invariant across time, we cannot assume that the corresponding latent statuses at the two time points were exactly the same. In general, latent status means in the first follow-up were slightly higher than that of the base year. We need to bear that in mind when interpreting latent status prevalence changes across time and transition probabilities between latent statuses across time.

The biggest differences in the prevalence of corresponding latent status across time were found in the *Low All* status and the *High All* status. The *Low All* status increased by 7.7%, whereas the *High All* status decreased by 5.2%. This suggests that students were more likely to switch to profiles characterized by lower math and/or science motivation than switch to profiles characterized by higher math and/or science motivation. The prevalence of *Higher Science* and *Higher Math* status were quite similar, with a decrease of only 1.1% and 1.2% respectively. However, this does not mean that almost all students in these two statuses remained in the same status across the years. This is perhaps because when some students moved from the *Higher Science/Higher Math* status to the other statuses, a similar number of students moved the other way round at the same time. To better understand whether individual students correspond to the same status over time (within-person stability) and the nature of the transition between latent statuses, there is a need to closely examine individuals' transition probability between latent statuses across time.

The latent transition matrix shows that the latent statuses were relatively stable, as most students (56.4%-66.8%) were more likely to stay in the same status than transition to another status. This is consistent with Lazarides et al. (2020) which found that the

math motivation profile was relatively stable from the beginning of 7th grade to 12th grade, and Wang et al. (2017) which found 63% of the participants had stable levels of ability self-concept and task value in physical science across 7th to 12th grade. Studies with variable-centered approaches also found that math self-concept, intrinsic value, and utility value were relatively stable from 9th grade to 10th grade (Lazarides & Lauermann, 2019), and confidence and self-efficacy in math/science were stable across the high school years (Gremillion et al., 2019). In the current study, students were most likely to transition to a status that was adjacent to their original status. It was unlikely for them to move from the lowest motivation status to the highest status, and vice versa. For instance, the probability of transitioning from the *Low All* status to the *High All* status was only 2.5%, and from the *High All* status to the *Low All* status was only 1.2%. The status with the lowest math and science motivation was the most stable. This is consistent with Lazarides et al. (2020), which found that students with low motivation were more likely to remain in the same profile than those with higher motivational beliefs profiles. This is perhaps because math and science courses become increasingly difficult in high school, and it is hard for students with low math and science motivation to increase their performance and motivation, especially those who have decided to pursue a non-STEM career in the future. Perceptions of teachers' beliefs and support could also influence student motivation. For instance, the more teachers believed that math ability is innate, the lower was the intrinsic motivation(similar to intrinsic value) of their low-achieving students (Heyder et al., 2020). Perception of teacher caring was a significant predictor for all motivational constructs in high school (Umarji et al., 2021). Perhaps students with low motivation in math and science also perceived lower levels of teacher support and caring

in math and/or science class, which further hindered them from increasing their motivation.

Consistent with Lazarides et al. (2019; 2020), both increase and decrease were found in students' math and science motivation levels. Increase in math and/or science motivation include transitions from the *Low All* status to any other status (34.2% in total), and transitions from the *Higher Science* or the *Higher Math* status to the *High All* status (15.4% in total). Decreases in motivation include transitions from *Higher Math* and *Higher Science* to *Low All* (37.6% in total) and transitions from the *High All* status to any other three statuses (43.6% in total). The different probabilities indicate that students' motivation was more likely to decrease than increase. Various reasons might contribute to the changes in motivation, such as classroom quality, gender stereotype beliefs (Barth & Masters, 2020), and students' psychological needs satisfaction from teachers and peers (Gnambs & Hanfstingl, 2016; Mata et al., 2012). Research found that if students' basic psychological needs for autonomy, competence, and relatedness were well supported, their intrinsic motivation could be increased across adolescence (Gnambs & Hanfstingl, 2016; Stiglbauer et al., 2013). However, secondary school teachers often enforce stricter discipline and provide fewer opportunities for students to be involved in decision-making than in elementary school, although adolescents' needs for autonomy support may be high (Anderman & Mueller, 2010). When students' need for autonomy support is not met, their intrinsic motivation is hard to increase. Besides, school climate, school composition (e.g., the percentage of students whose parent(s) has a college degree), high school policies (e.g., tracking, course sequence policies), and their peer groups could also influence students' math and science motivational beliefs (Jiang et al., 2020).

The transitions between the *Higher Science* status and the *Higher Math* status suggest that one's math and science motivation may change in different directions, although transition probabilities between these two statuses were relatively small (below 10%). For instance, one can start with relatively lower science motivation and relatively higher math motivation at the beginning of high school but end up with relatively higher science motivation and relatively lower math motivation towards the end of high school. This transition is characterized by increased science motivation and decreased math motivation. There were also transitions characterized by decreased science motivation and increased math motivation.

The extent of the changes in students' math motivation and science motivation was also different. For instance, students in the *Low All* status were more likely to transition to the *Higher Science* status (19.1%) than transition to the *Higher Math* status (13.0%). This difference in transition probability suggests that it might be easier for high school students to increase their science motivation than math motivation. It might be also easier to lose science motivation than to lose math motivation. For instance, the probability for students in the *Higher Science* status to transition to the *Low All* status was 23.1%. In comparison, the probability was 14.5% for students from the *Higher Math* status to transition to the *Low All* status. The complex pattern in math and science motivation transition further indicates the need to examine math and science motivation separately as indicators of motivation profiles and latent statuses.

Differences between male and female students in transition probabilities were also manifest. Male students were more likely to stay in the *High All* status than female students, and they were more likely to move from lower motivation statuses to higher

motivation statuses. On the contrary, female students were more likely to move from higher motivation statuses to lower motivation statuses. This sharp contrast shows that starting with the same motivation level (i.e., the same latent status), female students were more likely to lose motivation in math and/or science than male students during high school years. This finding suggests that it is important to closely monitor changes in math and science motivation, especially among female students, and design relevant measures to prevent or slow down such changes. Research with variable-centered approaches also had similar findings. For instance, girls' math interest decreased while boys' did not change through adolescence (Koller et al., 2001), and girls showed increasingly lower math ability self-concept compared to boys from middle school through high school (Pajares, 2005). One advantage of person-centered approaches is that they enable us to identify subgroups of individuals at higher risk of motivational declines, which can facilitate the development of more individualized interventions to increase student motivation (Wang et al., 2017).

5.3 CAREER ASPIRATIONS AS AN OUTCOME OF STUDENTS' MOTIVATION PROFILES

The current study seeks to understand how math and science motivation profile membership influences STEM career aspirations (broken down into traditional STEM and health occupations) and differences between male and female students in STEM career aspirations within and across profiles. The findings offer evidence that STEM career aspirations are influenced by the congruency of math and science motivation and gendered preferences for STEM fields. Consistent with findings from variable-centered approaches (e.g., Lauermann et al., 2017; Riegle-Crumb et al., 2011; Robnett & Leaper, 2013) and person-centered approaches (e.g., Anderson & Chen, 2016), students with

higher math and science motivations were more likely to be interested in traditional STEM careers and health occupations than those with lower math and science motivations. For instance, students in the *High All* profile were more likely to be interested in a traditional STEM career than students in all the other three profiles. Students in the *Low All* profile were less likely to be interested in health occupations than students in any other profiles.

One unique finding is that although there is no significant difference between students in the *Higher Science* profile and students in the *Higher Math* profile in traditional STEM career aspirations, those in the *Higher Science* profile were more likely to be interested in health occupations than those in the *Higher Math* profile. The *Higher Science* profile is characterized by relatively high science motivation and relatively low math motivation. This finding suggests that high school students were aware that different STEM careers had different requirements in math. If they were not good at math and/or had a lower interest in math courses, they could still plan to have a STEM career that does not have very high requirements for math. Previous research also found that students with lower math self-concept of ability in middle and high school were more likely to be interested in careers in Health, Biological, and Medical Sciences over traditional STEM careers (Wegemer & Eccles, 2019). As such, schools and parents should provide enough information and opportunities for adolescents to learn about the different STEM fields and their differential requirements in math and science. By doing this, high school students who originally may avoid a STEM career path due to lower math motivation may now be drawn to STEM fields that do not have very high math

requirements, such as health occupations, social and behavioral sciences (e.g., economics, political science, psychology, and sociology).

Consistent with previous studies, which found that as early as in adolescence, males and females demonstrated different occupational aspirations (Diekman et al., 2010; Eccles, 2009), the current study also found significant differences between male and female high school students. After controlling for motivation in math and science (i.e., within the same latent profile), 11^{th} grade female students in the *Higher Math* profile and the *High All* profile were still less likely to be interested in traditional STEM careers than male students in the same profile. On the other hand, female students in each profile were more likely to aspire for health occupations than male students in their profile. This is consistent with another research which found large gender differences in career plans, with boys showing much higher interest, particularly in engineering, while girls were more interested in careers in health occupations during their high school years (Sadler et al., 2012). The finding suggests that even when female students were confident about their ability in math and science and place high value on them, they were still less likely to be interested in traditional STEM careers. Meanwhile, regardless of their motivation level in math and science, female students were more likely to be interested in health occupations.

It is interesting to probe why male and female students have different career preferences. A meta-analysis on gendered vocational interests pointed out that females show stronger artistic, social, and conventional interests and prefer occupations that involve interacting with people, whereas males show stronger realistic and investigative interests and prefer occupations that involve working with objects, machines, and tools

(Su et al., 2009; Wang & Degol, 2013). Female students may have been deterred by the stereotypes associated with traditional STEM fields. For instance, the nerd-genius stereotypes (e.g., STEM professionals are nerdy geniuses, tech-obsessed, have no social lives, and are not romantic) affected females more than males' identification with STEM and their motivation to pursue STEM careers (Starr, 2018). Besides, females tend to put more value on jobs that involve helping others and benefitting society, while males place more value on jobs that allow them to make a lot of money, have power, and become famous (Cerinsek et al., 2013; Freund et al., 2013; Schwartz & Rubel, 2005). Because females tend to endorse communal goals (e.g., working with or helping other people) more than males, their interests in traditional STEM careers were disproportionately affected (Diekman et al., 2010). Compared to traditional STEM fields, health occupations involve more interactions with people and helping people, which may explain why female students prefer them. In addition, some studies found that the combination of high ability beliefs in both math and English signified a lower possibility of pursuing math/science-related careers. Since females placed a higher value on English than males, they were less likely to have math/science-related career plans (Lauermann et al., 2015). It might also be useful to help female students recognize their standing in math and science abilities and motivation relative to the male students, which may boost their confidence to pursue a traditional STEM career, as females tend to underestimate their ability to succeed in STEM fields (Correll, 2001; Sáinz & Eccles, 2012).

From the perspective of person-centered approaches, it is important to know a student's math and science motivation profile to understand his/her likelihood of being interested in a STEM career to be able to design targeted interventions to increase the

likelihood. Because students can have a motivation profile with remarkably different levels of math and science motivation and its implications for different STEM career aspirations, it is necessary to clearly define the purpose and strategies of the interventions. For instance, to increase students' interests in traditional STEM careers, the measures should be more towards identifying students whose motivation profile is characterized by lower math motivation and improving their math efficacy and values. Since female students within the *High All* and *Higher Math* profiles were still less likely to be interested in traditional STEM careers than male students, only improving their math motivation is not enough. One necessary strategy might be to help them discover the possibilities of helping people and benefiting society through a traditional STEM career (Diekman et al., 2010). Another measure might be to reduce the influence of negative stereotypes of STEM (e.g., being less people-oriented and masculine), because they have the potential to decrease students' STEM career interests (Luo et al., 2021; Makarova et al., 2019). Counter-stereotypical perceptions of STEM professionals (i.e., perceptions that scientists are individuals with talents and various interests who do not work in isolation) could positively motivate students' future plans in STEM fields (Nguyen & Riegle-Crumb, 2021). STEM interventions should also aim to reduce the nerd-genius stereotypes and the reminiscence of these stereotypes in classrooms (Starr, 2018).

Motivation interventions have been shown to improve students' competence-related beliefs, values, interests, and academic performance in STEM courses (Rosenzweig & Wigfield, 2016). Practical measures can also be taken in the daily learning context, such as the classrooms, to improve adolescents' math and/or science

motivational beliefs. Numerous research studies have documented effective measures to improve adolescents' science motivation, such as providing examples of science applications and science-related careers available (Aeschlimann et al., 2016), having a diverse range of activities in the class (such as science clubs or science field trips) (Taskinen et al., 2013), service-learning activities for high school students that focus on hands-on experiences and solving real-life problems (Collins et al., 2020), supporting students' self-concepts in science, and inclusive classroom practices (Bøe & Henriksen, 2013). These measures focused on one or more motivational aspects in science, such as students' expectancy in science, intrinsic or utility value of science, and were effective in improving students' science competencies, interest and values, and interest in STEM careers. More research is needed to explore the best practices to improve students' math motivation.

5.4 STABILITY OF STEM CAREER ASPIRATIONS AND CONSISTENCY BETWEEN CAREER ASPIRATIONS AND COLLEGE MAJOR SELECTION

Cross tabulation results suggest that high school students' career aspirations remained relatively stable from 9^{th} to 11^{th} grade, as 70% of them had the same career aspirations. It is interesting that 16% of the students switched from non-STEM career aspirations to STEM career aspirations. A slightly lower percentage (13%) of students switched from STEM to non-STEM career aspirations. This finding suggests that even though career interests are relatively stable for the majority of students through high school years, approximately one third of the students changed career aspirations across the three years of high school. A lot of factors might have contributed to the change except for transitions in math and science motivation profile, such as advanced math and

science course taking, good/bad teachers, and other experiences in and outside the classes.

Likewise, most students (62.6%) had chosen their first college major consistently with their career aspirations in 11th grade, which means those who wanted to have a STEM career in 11th grade chose a STEM major in college, and those who wanted to have a non-STEM career chose a non-STEM major. However, a considerable proportion of the students (27.9%) who indicated aspiring for a STEM career did not pick STEM as their first major. This proportion is higher than students who changed their career aspirations from STEM to non-STEM in high school. There were also students who wanted to have a non-STEM career but chose a STEM major, but the proportion was remarkably lower (9.5%). Except for the possible increase or decrease in math and/or science motivation, a lot of other factors may affect one's choice of college major, such as the major's job opportunities and potential for career advancement, the level of compensation in the field (Malgwi et al., 2005), potential income, parents' influence, teacher/professor influence (Stock & Stock, 2018), and sense of belonging in the STEM field (Rainey et al., 2018). This finding suggests that picking a first major in college becomes more complex for students than just maintaining their original career aspirations in high school.

Because of the nature of STEM jobs, if one does not study in a STEM major in post-secondary education, it is very hard for that person to have a career in STEM fields that requires a STEM degree or certificate. The possible instability of STEM career aspirations and the inconsistency between STEM career aspirations and STEM major selection imply that it is challenging for students to remain in the STEM pipeline. The

inconsistency in STEM career aspirations in 9th grade and 11th grade reveals that the leak is already obvious from high school, so educational efforts to maintain STEM career interests should begin at an earlier age than college. It must be noted that this study used the definition and categorization of STEM fields adopted by NCES, which considered health occupations, social sciences, and architecture as STEM subcategories. Therefore, those who left traditional STEM fields to go to other fields such as social sciences were still considered to remain in the STEM pipeline, which ensures a more accurate description of the transition between STEM and non-STEM fields. However, many students participated in the data collection in the second follow-up but did not provide information on their first major or field of study for the postsecondary degree/certificate (5,848 students in total). The best guess is that most of these students did not pursue further study beyond high school, but a few of these students might still have the opportunities to have a STEM career, such as computer support specialists, electrical installers and repairers, machinists, or veterinary assistants. Sometimes these STEM careers require only a high school diploma or a professional, high-quality portfolio of completed work instead of a degree.

5.5 LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

The data used for the current study were collected in 2009, 2012, and 2017. Although the sampled students could represent the students enrolled in high schools in 2009 in the United States, they may not well represent high school students in the United States in the 2020s. However, HSLS:09 is still the most recent nationally representative dataset available on high school students which focuses on understanding high school students' math and science experiences and how that influences students' STEM outcomes through college and the workplace. It takes enormous time, effort, and money

to collect a large-scale longitudinal dataset like this; therefore, it needs to be thoroughly studied. Future research could use more recent and smaller datasets to investigate similar questions and compare the findings with the current study.

The study examined the associations between STEM career aspirations and latent profile membership characterized by math and science motivational beliefs, but other factors might also play a significant role in influencing STEM career aspirations. For instance, adolescents' math ability belief became a weaker predictor of math/science-related career plans when their English ability belief became higher (Lauermann et al., 2015). Likewise, in another study, math expectancy and value beliefs also became a weaker predictor of STEM major selection when English expectancy and value beliefs were higher (Gaspard et al., 2019). As a result, students with high ability beliefs in math/science may not be interested in a STEM career because they are more interested in a non-STEM career. These findings highlight the importance of considering the combined influences of different domains on career plans (Lauermann et al., 2015). Particularly, future studies could include English motivational beliefs together with math and science and as latent profile indicators to see how they interactively influence STEM career aspirations.

Although the present study did not assume a causal relationship between math and science motivation profile and career aspirations, the auxiliary model was specified in a way that implies such a relationship. In the auxiliary model, profile membership is the predictor variable, and career aspiration is the outcome variable. Most existing studies have also examined math and/or science motivation as the predictor of career aspirations. However, for some students, their career aspirations might shape their math and science

motivation instead of the other way around. Moreover, some students may not be able to tell which one is the influencing factor. Future research can examine career aspirations as the predictor of math and science motivation profile, or examine the reciprocal relationship between career aspirations and math and science motivation profile for respondents who indicate such a relationship. Future research could also separate the three situations and find out which situation is more common.

Cost was not included as a profile indicator because the items used to form the cost variable were not the same at the two time points, and they were scaled in different ways (continuous variable at the base year and dichotomous at first follow-up), so it was hard to compare them across time and use them in the latent transition analysis. So far, only a few of the extant studies included perceived costs (e.g., Bøe & Henriksen, 2013; Conley, 2012; Lauermann et al., 2015) as a profile indicator, and the recent new measures of cost sometimes use the same labels to describe very different sets of items (Eccles & Wigfield, 2020). Future research should develop a measure that could better represent the multidimensional nature of the cost construct as described in EVT (Eccles & Wigfield, 2020) to better understand its effect on motivation profiles and potential influence on waning STEM motivation and career aspirations.

Latent transition analysis was used to explore the directions and nature of change in students' motivation profiles. However, measurement invariance tests could not find a good invariance model. Therefore, the study used the least restrictive constraint – measurement noninvariance (freely estimate the latent status indicator means across time) in the latent transition analysis. This assumption made the interpretation of transition probabilities between latent status across time not as straight forward as the LTA model

which assumed measurement invariance, because the latent statuses at each time point were not exactly the same. Future research should seek to do latent transitions with stronger measurement invariance and/or find more theoretical and practical support for assuming measurement noninvariance in LTA analysis.

The current study only descriptively modeled the stability of career aspirations during high school and the consistency between 11th grade career aspirations and first major in college. More complex statistical analysis may be used to model the trend and provide more reliable inferential statistics. Besides, only two categories – STEM and non-STEM – were included in the analysis. Health occupations were not separately examined because the first college major variable does not contain such a category. Future research can break down careers into more categories to describe the stability of STEM career aspirations more accurately. For instance, Sadler and colleges (2012) distinguished five broad career categories: non-STEM, science (such as physical, life, and earth sciences, mathematics), engineering (including computer science), medicine (such as physicians, veterinarians that require advanced degrees), and health (such as nursing, medical technicians), and studied how students' initial specific (disciplinary) career interests influenced the stability of their interest in a STEM career throughout high school[11]. Studying different STEM fields separately would also greatly facilitate the understanding of gender differences in STEM career interests. A different perspective on women's interest in STEM careers can be provided by disaggregating the STEM fields and using a broader definition of STEM, which includes the health occupations and other often excluded fields, such as social sciences.

[11] The Sadler et al. (2012) study did not consider medicine and health as STEM majors.

5.6 CONCLUSIONS

This study extends previous literature on STEM career aspirations by using person-centered approaches to examine how high school students' math and science motivation profiles influence career aspirations with a nationally representative dataset. It is one of the few studies that examined high school students' motivation profiles characterized by both math and science expectancy and values. The results revealed latent profiles with similar levels of math and science motivation and profiles with distinctly different levels of math and science motivation. Math and science motivation carry different weights in the associations between latent profile membership and aspirations in traditional STEM and health occupations, which calls for future research to examine both math and science motivation when studying the implications of math and science motivations. The study also used latent transition analysis to explore the possibility and directions of change between different profiles across high school years. The transition matrix demonstrated the relatively stable nature of math and science motivation profiles and revealed transition probabilities between different profiles, which cannot be shown with variable-centered approaches. Female students were more likely to be in lower motivational profiles, more likely to transition to lower motivation profiles, more likely to be interested in health occupations and less likely to be interested in traditional STEM careers, which signals the direction for future research toward improving female students' math and science motivation and interest in traditional STEM careers.

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