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Expectancy-Value Profiles in Math and Science: A Person-Centered Approach to Cross-Domain Motivation with Academic and STEM-Related Outcomes

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Abstract:
The need to enhance the STEM workforce and, in turn, the STEM educational pipeline is a prevailing issue in the U.S. One critical component in this pipeline is students' interest in STEM majors and their persistence in such majors, theorized to be a function of both students' perceived value and expectancy beliefs in the subject matter. Using an expectancy-value lens, we examined cross-domain patterns of high school students' expectancy beliefs and values in both mathematics and science using a person-centered or profile approach. With data from the High School Longitudinal Study, latent profile analysis revealed five profiles characterized as *Low Math/Low Science* (i.e., endorsing 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*. Taking into account aspects of students' background and school context, we found that motivational profile membership predicted math and science high school achievement, college persistence, and both STEM major intentions and decisions. Moreover, there were a number of gender and racial/ethnic differences and contextual variation in profile memberships as well. Implications for theory and educational practice are discussed in relation to study findings.

Keywords: STEM, Expectancy-value theory; latent profile analysis; high school; college; motivation

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Increasing and broadening participation in STEM (Science, Technology, Engineering, Mathematics) disciplines has been an enduring concern in the United States. A balanced and more diverse STEM workforce is essential for the U.S. to meet growing demands alongside rapidly developing economies around the globe (National Science Board, 2018). Of particular interest to educational researchers has been the role of malleable factors such as students' motivation toward math and science in students' STEM educational pathways (Cromley et al., 2016; Eccles, 2005; Wang, 2012). A mounting body of literature supports the positive links between various STEM-related outcomes with students' beliefs and perceptions informed by expectancy-value theory (e.g., Lauermann et al., 2015; Umarji et al., 2018; Wang & Degol, 2013). As a dominant theory in motivation, expectancy-value theory (EVT) emphasizes how students' expectancies of success and their values toward academic tasks drive students' educational choices (Eccles et al., 1983; Eccles & Wigfield, 2020; Wigfield & Eccles, 2000; 2020), such as pursuing STEM-related majors and careers. However, many EVT studies have relied on variable-centered approaches that measure how different forms of variables uniquely and independently predict student outcomes (Guo et al., 2018). In contrast, person-centered approaches allow the integration of motivational qualities to shape academic outcomes and to consider simultaneous variations among multiple motivational indicators within students.

EVT person-centered (or person-oriented) approaches often generate profiles to uncover the various ways individuals tap into expectancies and task values organized as intraindividual hierarchies (e.g., Rosenzweig & Wigfield, 2017). Eccles (2009) defined intraindividual hierarchies as the relative levels of students' expectancy beliefs and subjective task values across domains. Although these person-oriented approaches in motivation are growing in popularity (e.g., Fong et al., 2018; Wormington & Linnenbrink-Garcia, 2017), most profile-based studies drawing from EVT focus within a single domain such as math (e.g., Lazarides et al., 2020; Musu-Gilette et al., 2015). Among studies examining students' expectancies and values across multiple domains, STEM fields such as math or science are often contrasted with languages, such as English (Gaspard et al., 2020; Guo et al., 2018). These cross-domain comparisons assume that students choose STEM-oriented majors and careers based on their relatively weaker motivations for more language arts domains such as English (Eccles, 2009). However, this hypothesis does not fully account for students in STEM pathways with skills and interests in language arts (Wang & Degol, 2013) and the importance of verbal abilities in subjects like mathematics (Aiken, 1971; Wang et al., 2013). An alternative hypothesis guiding the current study lies in the driving force of *joint* motivations in both math and science domains. Given the centrality of valuing both math and science for STEM interest (Funk & Parker, 2018; Simpkins & Davis-Kean, 2005), a specific focus on expectancies and values for math and science and how they function together in synergistic or compensatory ways to motivate STEM interest is needed. Previous studies have not fully examined (a) cross-domain profiles in both math and science specifically and (b) how membership in these profiles predict high school student achievement, academic persistence, and STEM major intentions and choices. Doing so would contribute to our knowledge of students' hierarchies of individual expectancies and task values in a wider array of domains (Gaspard et al., 2019).

Therefore, in a nationally representative sample of high school students, we investigated latent profiles of students' expectancy and value beliefs in math and science. In particular, we examined how domain-specific expectancies and task values (intrinsic value, attainment value, and utility value) in both math and science function together intraindividually in contrast to separate math profiles and science profiles. We next explored sociodemographic characteristics such as students' gender and race as antecedents of latent profile membership, given the underrepresentation of students of color and women in most STEM fields. Lastly, we tested if profile membership predicted a set of student outcomes including high school achievement in math and science, academic persistence, high school intent to major in STEM, and STEM major choice in college.

Literature Review

Expectancy-Value Theory

As the basis for our study, expectancy-value theory (EVT) is one of the most influential motivational frameworks in education (Eccles et al., 1983; Wigfield & Eccles, 2000; 2020). Grounded in what a student is psychologically thinking (Eccles, 2006), EVT emphasizes how students' perceptions are shaped over time by various personal factors or influences from different socializing agents (Eccles & Wigfield, 2002). These perceptions, in turn, can influence academic decision-making and achievement outcomes. In modern conceptions of EVT, there are two major kinds of beliefs, both of which are shown to be highly domain-specific (Trautwein et al., 2012). The first set of beliefs are expectancies, defined as students' beliefs about how well they will do on future tasks. Motivation scholars have likened expectancy to self-efficacy, defined as the personal judgment of their capacities to produce specific performance attainments (Bandura, 1997), or to academic self-concept, defined as one's perception of one's general ability in school (e.g., Shavelson et al., 1976). Given the substantial overlap among these constructs (Anderman, 2020; Linnenbrink-Garcia et al., 2016; Wigfield et al., 2020), we reference prior research using these variables in our review of literature to operationalize expectancy beliefs.

The second set of beliefs encompasses the degree to which individuals value specific tasks or domains. EVT posits that there are four major categories of subjective task values: intrinsic value, attainment value, utility value, and cost (Wigfield & Eccles, 2000). First, intrinsic value refers to inherent enjoyment gained from the task and bears conceptual similarity to intrinsic motivation from self-determination theory (Anderman, 2020), which posits that intrinsic motivation pertains to activities done for their inherent value (Ryan & Deci, 2020). Second, attainment value has been traditionally defined as the task's perceived personal importance and more recently considered to reflect more of an identity-based importance (Eccles & Wigfield, 2020). In our study, we adopted a revised conceptualization of attainment value by Eccles (2009), where she stated, "In the past, I conceptualized attainment value in terms of the needs and personal values that an activity/behavior or task fulfills. Today I am conceptualizing it more in terms of personal and collective identities" (p. 83). Third, utility value is the perceived relevance or usefulness of a task with regard to a student's future. Fourth, cost is generally conceptualized as the time and energy which must be given up in order to participate in an activity (Eccles, 2009). Cost was not included in our study due to the unavailability of items in the dataset, which we discuss in our limitations section.

Expectancy-Value Theory with STEM-Related and Academic Outcomes

Previous studies have emphasized how students' expectancies and values influence student outcomes and choices associated with STEM as well as academic outcomes such as academic persistence (Schnettler et al., 2020). Specifically, with regard to expectancy beliefs in STEM disciplines, high school students' perceived abilities in mathematics have been positively linked with future math course enrollment and math- or STEM-related occupation interests (Wang, 2012; Wang et al., 2013). Among college students, STEM major selection was positively linked with students' expectancies (Sax et al., 2015; Wang, 2013). Although math expectancy beliefs have been more widely studied, prior studies have also indicated the salience of science expectancy for predicting STEM-focused career plans (Anderson & Ward, 2013).

In general, higher subjective task values associated with math or science shape the academic choices that can lead to progress in the STEM career pipeline (Eccles et al., 2004; Robinson et al., 2019), including outcomes such as STEM course enrollment, mathematics achievement, and STEM career aspirations

(Updegraff et al., 1996). For instance, intrinsic value for science was positively associated with higher STEM course enrollment (Watt et al., 2006), and science utility value positively predicted STEM career choices (Maltese & Tai, 2011). Similar patterns of results have been found with math intrinsic value and utility value (Fong & Asera, 2010; Wang, 2012). Math attainment value at the beginning of high school was a positive predictor of math achievement and intent to major in STEM at the end of high school (Fong & Kremer, 2020).

Although a relatively clear picture exists of the independent linkages between students' motivational beliefs and a variety of STEM outcomes, the influence of expectancy-value interactions on student outcomes is unclear, despite it being a main focus in Atkinson's (1957) original model. Most research studies have either neglected these theorized multiplicative terms in their analyses (c.f., Nagengast et al., 2013) or presented inconsistent results regarding how these interaction terms influence student outcomes, including many nonsignificant interaction effects (see Wang et al., 2013). Also, it is unclear whether EVT interactions have a synergistic effect—that is, a student's motivation is high only if both expectancy and task value are high—or a compensatory effect—when one of the expectancy components compensates for the value component when predicting student outcomes, or vice-versa (Guo et al., 2016). To further investigate how the interactions of expectancy and value beliefs operate at the intraindividual level and across multiple domains, person-centered approaches may provide critical insights.

Person-Centered Approach Drawing from Expectancy-Value Theory

Investigations of interactive effects via a person-centered approach (Bergman & El-Kouri, 2003; Bergman & Trost, 2006) allow the examination of the complex reciprocity among motivation variables (Shell & Husman, 2008). Studies using a profile approach identify coherent and coordinated patterns of motivations that inform a learner-centered approach. For instance, Conley (2012) provided a powerful example of employing a person-centered approach to examining learners' co-occurring competence beliefs, task values, and achievement goals. In a sample of diverse middle school students, Conley generated seven clusters from various motivational factors based on achievement goal and expectancy-value perspectives. Results indicated that integrating motivational perspectives had more explanatory power than just using a goal orientation perspective alone to influence outcomes such as students' academic achievement measured by a state standardized math exam and positive affect.

There have been a number of EVT person-centered studies on academic outcomes and career aspirations in a variety of disciplines. Given our focus on motivational beliefs in math and science, our study builds upon the emerging group of person-centered studies involving these STEM-related domains (e.g., Anderson & Chen, 2015; Bøe & Henriksen, 2013; Simpkins & Davis-Kean, 2005). As a recent example, in postsecondary science courses, Perez et al. (2019) identified motivational profiles using expectancies, values, and costs. Latent profile analysis revealed three profiles during students' first semester in college: (1) Moderate all; (2) Very high competence/values with low effort cost; and (3) High competence/values with moderate costs. Compared to the latter two profiles, the first profile of students (Moderate all), consisting of a larger proportion of underrepresented minority students, completed less STEM courses and had lower STEM achievement. Examining math motivational beliefs from middle to high school, Lazarides et al. (2020) used latent profile analysis to identify four stable profiles using expectancy, intrinsic value, and importance (utility and attainment values combined). Three profiles with expected mean differences in motivational beliefs (low, medium, high) emerged along with a fourth profile with a different configuration of intraindividual levels (low intrinsic value with medium importance and expectancy). In general, in relation to other profiles, the low motivational beliefs profile had consistently lower levels of math achievement and consisted of fewer math-related majors. Individuals in this profile had less math-related occupational plans and had fewer math-related careers 22 years after high school.

Although various patterns of expectancy-value beliefs within a single domain have been uncovered, our interests lie at the intersection of both math and science domains. A few studies have examined both of these domains together but only by creating separate profiles for math and for science. For instance, Simpkins and Davis-Kean (2005) used cluster analysis to identify four distinct groups of students based on self-concept and values in math and science, separately. In both math and science domains, they identified the same pattern of four clusters: (1) both self-concept and value high; (2) high self-concept; (3) both moderate; and (4) both low. A similar approach has been taken among gifted or high ability populations as well (Anderson & Cross, 2014). In both of these studies, the same profile solution and pattern of results were found for math and science. However, it is unclear what profiles will emerge when multiple, domain-specific motivational beliefs are combined together in the same analysis, specifically with regard to math and science domains.

Prior person-centered studies integrating motivational beliefs of multiple subjects together in cross-domain profiles have included either a sole focus comparing math to language-oriented subjects (e.g., English) or using a broader set of subjects including math and science among other domains. Under the assumption that students pursue STEM educational pathways when motivational beliefs toward math outweigh motivational beliefs in language arts such as English (see Eccles & Wigfield, 2020), researchers have examined cross-domain profiles combining math and English expectancies (Umarji et al., 2018) or expectancies, values, and costs in math and English (Gaspard et al., 2019). While these intraindividual hierarchies of expectancies and values across math and English are powerful mechanisms through which students decide to pursue STEM careers, the intraindividual levels of beliefs toward math and science may also factor into students' propensity toward engaging in STEM. In the current study, we explore this possibility and heed a recommendation by Gaspard et al. (2019): "Future research might investigate expectancies and values in a broader set of domains to deepen the understanding of intraindividual hierarchies across domains and how they predict students' academic choices. When investigating STEM majors, students' expectancies and values in the sciences might also be of interest" (p. 160).

To our knowledge, only a handful of EVT-based profile studies have included math and science domains but often do so in conjunction with other domains (e.g., Viljaranta et al., 2009). For instance, measuring task values for subject domains in languages, math and science, social sciences, and practical subjects (e.g., music and physical education), Chow and Salmela-Aro (2011) distinguished between adolescent profiles varying in subjective task values (importance, usefulness, and interest) toward math and science as a combined domain from profiles with higher interest in just practical subjects or all subjects. In a subsequent study among Finnish secondary students, Chow et al. (2012) created profiles based on subjective task values in math and science combined, practical subjects (arts and physical education), and language (i.e., Finnish). There were three identified groups: (1) High math and science; (2) No preference; and (3) Low math and science. In both studies however, combining math and science together into one domain restricted the measurement of subject-specific values in math and science from freely varying within each individual. Partly addressing this issue, Chow et al. (2012) also examined U. S. high school student attainment, intrinsic, and utility task values associated with English, math, and physical science (as separate subjects). Across these domains, the three generated profiles only differed in task values for math and science: (1) High math and science; (2) Moderate math and science; and (3) Low math and science. Levels of task values for English were fairly equivalent in all groups. Although this study provided initial evidence of how math and science value beliefs function together even when treated as separate indicators, we include the additional component of expectancy beliefs as well as an expanded set of outcomes in the current study.

In summary, EVT profile studies have either examined math and science domains separately (Andersen & Ward, 2013; Lazarides et al., 2020; Perez et al., 2019; Simpkins & Davis-Kean, 2005; Watt et al., 2019) or included other domains such as language (Gaspard et al., 2019). Other profile studies exclusively focus on subjective task values for math and science domains along with subjects such as social sciences, arts and physical education, and language (Chow et al., 2012; Viljaranta et al., 2009) or on expectancy beliefs in math and English (Umarji et al., 2018). However, a clear focus on cross-domain profiles in math and science using both expectancy and value beliefs is conspicuously absent despite the importance of both math and science in STEM-related pursuits (Funk & Parker, 2018). Furthermore, treating math and science as separate domain indicators may allow the possibility of student profiles that favor motivation for math over science, or vice-versa. This additional nuance may inform motivational mechanisms for how beliefs toward both subjects shape their interests and outcomes associated with STEM. Moreover, to continue building on other EVT profile studies that examine the gender disparities in STEM attainment (e.g., Chow et al., 2012; see Wang & Degol, 2013), we also examined demographic and contextual antecedents of profile membership, with a particular focus on gender and race/ethnicity, given the underrepresentation of women and people of color in many STEM fields (e.g., Cheryan et al., 2016; National Science Foundation & National Center for Science and Engineering Statistics, 2019; Seymour, 1995).

The Role of Cultural Milieu and Motivationally Supportive Environments

Central to EVT and more so with the newly renamed situated expectancy-value theory (SEVT; Eccles & Wigfield, 2020) is the role of situative or contextual factors such as the cultural milieu through which students begin to make sense of roles, goals, and socializers, that together in turn shape their expectancies and values. Although this complex set of developmental factors tends to be difficult to measure, we were specifically interested in the role of gender and race/ethnicity in our current study, especially given the underrepresentation of women and students of color in most STEM fields. Expectancies and task values in a variety of disciplines including STEM fields have been examined with regard to gender differences (Wang & Degol, 2013) and culture (Tonks et al., 2018), but how these sociodemographic factors influence cross-domain motivation profiles is under-examined. Another situative factor of interest is the kind of motivationally supportive environments instructors and schools can create for students. Teachers are important socializers who can shape the perceptions of students regarding their expectancies and values (Eccles & Wigfield, 2020; Parrisius et al., 2019). In the current study, we included variables assessing the degree to which high school teachers emphasized the enhancement of interest in math and science and percent of college-bound students as potential contextual factors for students' outcomes and profile membership. In addition, school norms and peers are also important socializing forces (Kremer et al., 2018). Given our interest in postsecondary outcomes, the percent of college-bound students was included in our study to serve as a proxy for a college-going school culture that may motivate higher attainment outcomes (Engberg & Gilbert, 2014). We hypothesized that situational cues in students' learning environments, such as the degree to which their teachers value learning STEM-related subject matter and the extent to which their peers attend college after high school, might determine what is valued in their classrooms and schools and, in particular, shape their motivations toward math and science domains in high school and beyond (see Muenks et al, 2020).

Present Study

Given the importance of math and science in prerequisite courses for postsecondary STEM majors (Simpkins & Davis-Kean, 2005) and the link between both math and science motivations in K-12 settings and future STEM occupations (e.g., Funk & Parker, 2018), examining motivational beliefs in both of these domains is critical. Using the High School Longitudinal Study of 2009 (HSLS:09) dataset, a nationally representative dataset from the U.S., our study was guided by the following research questions: (1) What are the cross-domain profiles of students' expectancy and value beliefs in math and science among high school students? (2) Do math and science achievement, rates of academic persistence, and intention and choice of STEM major in college differ as a function of intrapersonal profile membership? (3) How well do variables such as students' gender and race predict profile membership? For the second research question, we included a wide range of outcomes relevant to students' progression in the STEM pipeline that extend beyond prior EVT studies that solely focus on choosing a STEM major or career (Chow et al., 2011). Given EVT's focus on achievement-related choices and performance over time, we included outcomes relevant to college-bound students' last year of high school and their academic progress at a postsecondary institution. Students' high school achievement in math and science, particularly in higher level coursework, has been shown to be important predictors of postsecondary degree attainment in STEM (Tyson et al., 2007). Moreover, high school grades in math and science courses often determine what kinds of STEM courses they can enroll in while in college (e.g., Ngo & Kwon, 2015). In addition, we also measured students' academic persistence both in college for the first three years after graduating high school and both their intentions to major in STEM and their choice of a STEM major in college. These outcomes are particularly important in light of the low academic persistence rates among STEM majors (Graham et al., 2013).

For the second and third research questions, we also controlled for a number of demographic and school-related covariates, but of particular interest was the role of motivational contexts. To explore how teachers' motivational influences along with profile membership may be associated with student outcomes, we examined teacher emphasis on increasing math and science interest (see Byrnes & Miller, 2007) as well as the percentage of college-bound students at their respective high schools. Including such contextual factors along with intraindividual profiles provides a more nuanced and holistic picture of the motivational dynamics occurring both within and surrounding individual students.

In sum, the present study examines high school students' cross-domain motivation profiles in math and science and how expectancy and value beliefs in these two domains may vary intraindividually, in contrast to the large majority of studies that focus on variable-centered approaches (e.g., Fong & Kremer, 2020). One of the main contributions of this approach is to first extend prior studies on math- and science-specific profiles separately (Andersen & Ward, 2013). Combining these two domain-specific motivations together through a person-centered approach offers greater insight into how they may jointly function within students, as separate rather than combined domains (Snodgrass Rangel et al., 2020). Second, although cross-domain motivation profiles have been explored for math and English domains (Gaspard et al., 2019, 2020), our study extends work on intraindividual hierarchies of expectancies and values for two STEM-related fields. Third, our study's addition of math- and science-specific expectancy beliefs improves on prior work that focuses on student profiles of task values across domains (Chow et al., 2011, 2012) by examining together these two sets of beliefs central to EVT. Fourth, we innovate beyond prior research by measuring a larger range of academic and STEM-related outcomes associated with profile membership and including contextual predictors that may contribute to students' motivational development.

Method

Data and Sample Selection

Our study sample included individuals who had both engaged in postsecondary education and participated in the High School Longitudinal Study of 2009 (HSLS:09). The HSLS:09 included a nationally representative group of 23,000 high school students surveyed across four waves. Along with surveying students, their school administrators, math teacher, and science teacher were also surveyed totaling 929 school administrators, 17,882 math teachers, and 16,269 science teachers across the full sample of participants. The HSLS:09 focused on students' academic and career trajectories from ninth grade into postsecondary education and has been used to examine students' STEM-oriented motivational beliefs (e.g., Anderman et al., 2018; Andersen & Ward, 2013; Fong & Kremer, 2020). The sampling process occurred in a stratified, two-stage random sample design (Ingels et al., 2013). In 2009, the first wave of data was collected when students were enrolled in grade 9. The most recent wave of available data was collected in 2016, three years after on-time high school graduation. The present study used the HSLS's public-use dataset from four waves of the HSLS:09: Wave 1) base year survey in 2009; Wave 2) first follow-up in 2012; Wave 3) 2013 update; and Wave 4) second follow-up student interview from 2016. High school transcripts were also collected following their senior year of high school.

Given the present study's focus on latent profiles of STEM motivation and high school transition and college outcomes, students who had not completed any postsecondary coursework by the second follow-up three years after high school graduation were removed from analyses. This resulted in a sample size of 7,237 students (53.11% women). White students made up the majority (56.21%), followed by Hispanic students (20.82%), Black/African American students (9.26%; we will use term Black/African American throughout manuscript), Asian students (5.06%), and students indicating Other for race (8.65%). Nearly half of students had parents with a bachelor's degree or higher and an annual income greater than $75,000. Students attended schools that had an average of 78.25% students attending college after high school and participated in classrooms where the vast majority of teachers placed a moderate to heavy emphasis on increasing math and science interest.

Measures

Questionnaires were developed by HSLS:09 study staff and reviewed by a Technical Review Panel of both technical and methodological experts. Survey items were field tested and subsequently re-evaluated by the Technical Review Panel. Because measures were collected via student self-interviews, the Likert-scale items were constructed with second-person pronouns. Similar construction in item wording is reflected in prior literature (Cass et al., 2011; Means et al., 2017). Moreover, our study's approach was aligned with other educational psychologists who have used HSLS items in STEM motivation studies (e.g., Anderman et al., 2018).

Latent Profile Indicators

During the 2012 follow-up of the HSLS:09, when students were in grade 11, students completed psychological questionnaires to gauge their attitudes toward math and science along with attitudes toward their grade 11 math and science courses. Given differences in school requirements and course options, students completed various math and science courses. With regard to math courses during grade 11, 48% of students completed Algebra, 20% completed Calculus or Pre-Calculus, 14% completed Geometry, 10% completed Trigonometry, and 8% completed another type of math course. Sixty-three percent of grade 11 math courses were classified as honors or advanced while 13% were Advanced Placement courses. With regard to science courses in grade 11, 33% of students completed Biology, 23% completed Chemistry, 11% completed Physics, 10% completed Physical Science, and 23% completed another type of science course. Sixty percent of grade 11 science courses were classified as honors or advanced while 18% were Advanced Placement courses.

Students indicated their level of agreement with a series of statements using a Likert scale with four options: 4 = *Strongly agree*, 3 = *Agree*, 2 = *Disagree*, or 1 = *Strongly Disagree*. Following data collection, HSLS:09 study researchers created and validated four psychological scales of math motivation and four psychological scales of science motivation using principal components factor analysis. Specifically, SAS® *proc factor* was used to create the scales, weighted and standardized to have a mean of zero and standard deviation of one.

Using EVT as our theoretical framework, we selected scales that measured three subjective task values (intrinsic value, attainment value, and utility value) and one scale for expectancy for success. These scales were domain-specific for both math and science separately. Any negatively worded items were reverse-scored. We then standardized the previously constructed scales to have a mean of zero and standard deviation of one. See Table 1 for intercorrelations and Table 2 for means and standard deviations.

Subjective Task Values. Math intrinsic value and science intrinsic value included agreement with four statements regarding their intrinsic task values in their grade 11 math and science courses: "You are enjoying this class very much," "You think this class is a waste of your time," "You think this class is boring," "You are taking this class because you really enjoy [Math OR Science]." Intrinsic value further included whether students listed math or science as their favorite or least favorite subject. Reliability scores for the intrinsic value scales (5 items) were acceptable for math intrinsic value ($\alpha = 0.69$) and for science intrinsic value ($\alpha = 0.77$). A measure for attainment value assesses the degree to which the subject aligns with one's self-image or identity. Because the items we used captured the centrality of math and science to a student's identity (rather than in relation to the value of mathematics or science), this measure served more as a proxy for attainment value instead of assessing attainment value directly. Items included "You see yourself as a [math OR science] person" and "Others see me as a [Math OR Xcience] person." Reliability scores for the attainment value scales (2 items) were high for math attainment value ($\alpha = 0.88$) and science attainment value ($\alpha = 0.89$). Math and science utility statements included three items that assessed the usefulness of mathematics and science: "[Math OR Science] is useful for everyday life," "[Math OR Science] will be useful for college," and "[Math OR Science] is useful for a future career." Reliability scores for the utility scales (3 items) were acceptable for math utility value ($\alpha = 0.82$) and science utility value ($\alpha = 0.82$).

We conducted our latent profile analysis with all three task values for math and for science as separate latent factor indicators; levels of all three task values did not meaningfully distinguish profiles. Thus, we also created a math value scale using principal components factor analysis with the three math value subscales (intrinsic value, attainment value, and utility value). Due to the equivalent patterns of findings, we reported results using both individual subscales and the composite subjective task value measure, which averaged all three task value scales together.

Expectancy of Success. Expectancy of success in math and in science was measured using the HSLS:09 self-efficacy scales. These items were more analogous to performance expectations as conceived by EVT, rather than how self-efficacy is generally assessed which is at a more microanalytic level (Pajares, 1996). The scale comprised of four statements with specificity toward their math and science courses: "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," and "You are confident that you can do an excellent job on assignments in this course." Reliability scores for the expectancy scales (4 items) were high for math expectancy ($\alpha = 0.89$) and excellent for science expectancy ($\alpha = 0.92$).

Outcomes and Covariates

Achievement and Academic Persistence

Students' grade 12 GPAs in mathematics and science were collected from their high school transcripts and ranged from 0.25 to 4.00. GPAs were calculated from course grades in high school math and science courses. We also measured academic persistence in college using the 2016 second follow-up (three years following on-time high school graduation). Based on the 2016 interview, if students were either still enrolled in postsecondary courses or had completed a college degree, they were coded as persisting in college. If they were no longer enrolled in postsecondary coursework nor had completed a college degree, they were coded as non-persisting.

STEM Major Intentions and Choice

Obtained in 2012 (the spring semester of students' expected high school graduation year), students were asked whether they intended to pursue a STEM major upon entering postsecondary education. In the 2016 second follow-up three years after high school graduation, students were asked if their current major was in a STEM field. For both outcome variables, majors were classified using the U.S. Department of Education's Classification of Instructional Programs, 2010 edition (NCES, 2010).

Because a shift from major intention and major choice may represent a potential motivational shift, we calculated change in STEM major based on student responses to their STEM intentions in grade 12 and whether they were majoring in a STEM field three years later. We identified four groups of students: 1) students who intended to major in a STEM field in grade 12 and were majoring in a STEM field three years later; 2) students who intended to major in a STEM field in grade 12 but were not majoring in a STEM field three years later (dropped STEM); 3) students who did not intend to major in a STEM field in grade 12 and were majoring in a STEM field three years later (added STEM); and 4) students who did not intend to major in a STEM field in grade 12 and were not majoring in a STEM field three years later. For analyses including the change in STEM major variable, 4,990 students who had no intentions to major in STEM and did not major in STEM were dropped from analyses. This allowed us to compare students whose STEM intentions were consistent with major selection from grade 12 to three years later with those who dropped their STEM intention and those who added a STEM major while in college.

Contextual Variables

School characteristics included the percent of graduating high school students attending some form of postsecondary education, i.e., a proxy for the college-going culture at the school. School administrators during 2012 follow-up interviews when participants were in grade 11 provided these data. We also examined teachers' emphasis on increasing students' interest in math and science, based on interviews with students' math teacher and science teacher from base year surveys in 2009. In teacher surveys, math teachers and science teachers reported on their level of emphasis in increasing students' interest in mathematics and science, respectively, for the course in which the identified student was enrolled. Response options for this single item consisted of "no emphasis," "minimal emphasis," "moderate emphasis," and "heavy emphasis."

Covariates

Demographic and contextual variables were included as antecedents for profile membership and covariates to predict student outcomes. For student characteristics, we included race/ethnicity and gender. Parent characteristics consisted of parents' highest level of education and combined family income. Covariates were collected in 2011 during the second wave of data collection.

Analytic Approach

Using our sample of students who had engaged in postsecondary coursework, statistical analyses were employed in several steps. First, latent profile analysis (LPA) was carried out to identify latent profiles using the patterns of observed indicators. LPA is a statistical procedure in which individual cases are assigned to underlying subgroups based on input variables. For the present study, we used expectancies and values for math and science as input variables. The latent profiles were conducted through a series of models with the robust maximum-likelihood estimator ranging from 1 to 6 classes using Stata 16.1/IC (StataCorp, 2019a). To select the best fitting model, the Bayesian Information Criterion (BIC) and entropy were considered. Lower BIC values and higher entropy values indicate better model fit (Celeux & Soromenho, 1996). BIC values were the key referencing indicators given their high reliability for model fit (see Nylund et al., 2007). Entropy values (ranging from 0 to 1) indicate classification accuracy with values greater than .70 as preferable (Reinecke, 2006). We also took into consideration sample sizes of profiles and theoretically compatible solutions. By referencing other EVT-based profiles from prior studies (i.e., Andersen & Ward, 2013; Chow et al., 2011, 2012; Gaspard et al., 2019), we triangulated our proposed profiles, aiming for the most parsimonious solution that aligned with past research and forming clusters of students of substantive sample size. After the latent profile solution was identified, students were assigned to profiles based on the probability of membership as indicated by the model, with students assigned to the cluster with highest membership probability. To label each profile, we evaluated the relative scores of the indicator variables among the profiles.

Profile membership was, in turn, used to examine associations with student STEM and college outcomes. Math GPA and science GPA were predicted from profile membership and covariates using linear regression. College persistence, STEM major intentions, STEM major choice, and change in STEM majors were predicted from profile membership and covariates using logistic regression. Analyses utilized probability sampling weights and a Taylor series linearization to adjust standard errors of estimates for complex survey sampling design effects.

To maximize the analytic sample and account for missing data, multiple imputations were utilized for participants with missing information on a college outcome or a covariate. Compared to conventional approaches such as listwise deletion, in which observations with data missing on any variable are removed from analyses, multiple imputation allows for observations with missing data to be included and has been found to be less biased (Allison, 2001). Fundamentally, data imputation is a process wherein missing data are substituted for a set of reasonable estimates by predicting values for missing cases using observed values on the other variables in the model. For the present study, 20 imputed datasets were created. StataCorp recommends a minimum of 20 imputations to reduce sampling error (StataCorp, 2019b). Statistical analyses were performed on all 20 datasets and combined using Stata's standard multiple imputation procedures which accounts for uncertainty within predicted values.

Results

Identification of Latent Profiles

Based on statistical analyses of the latent models, the five-profile solution emerged as the best fitting model. Specifically, as Figure 1 indicates, the BIC and entropy scores began to flatten out from the four-profile to five-profile solution. There was minimal reduction in scores from the five-profile to six-profile solution. While the BIC scores improved most significantly from the one-profile to two-profile solution, our theory indicated that the sample would not fall into two homogenous groups. The five-profile solution had more theoretical support and was more aligned with prior research. Although most of the sample fell into either Profile 4 (48%) or Profile 5 (29%), the remaining sample in Profile 1 (11%), Profile 2 (6%), and Profile 3 (7%) represent distinct groups when considering students' math and science motivational beliefs. To further understand the relationships between the indicators, we calculated correlations (see Table 1) that revealed all indicators to be significantly correlated to one another ($p < 0.001$). As expected, the indicators related to math had stronger correlations to one another while the indicators related to science had stronger correlations to one another. The relatively lower correlations between math and science motivation variables provides additional justification for the existence of profiles with differentiated levels of motivation for these two domains.

The standardized values of the indicator variables by profile are displayed in Figure 2, and Table 2 displays means and standard deviations of indicator variables by profile. The five-profile solution consisted of Profile 1: *Low Math/Low Science* (n = 769, 10.63%), characterized by students' relative low math value and expectancy and low science value and expectancy; Profile 2: *High Math/Low Science* (n = 453, 6.26%), was comprised of students with high math value and expectancy yet low science value and expectancy; Profile 3: *Low Math/High Science* wherein students reported low math value and expectancy and high science value and expectancy (n = 485, 6.70%); Profile 4: *Moderate Math/Moderate Science* with students moderately motivated in math and science (n = 3,455, 47.74%); and Profile 5, consisting of students highly motivated in both math and science, the *High Math/High Science* (n = 2,075, 28.67%).

Sociodemographic and Contextual Characteristics of Profiles

Descriptive Statistics

Table 3 displays sociodemographic characteristics of each latent profile. The *High Math/Low Science* profile had the highest proportion of women (64.32% of profile), while the *High Math/High Science* profile had the lowest proportion of women (43.73% of profile). The lowest proportion of White students was in the *High Math/Low Science* profile (45.88% of profile). The *Low Math/Low Science* profile had the fewest Asian students (3.13% of profile). To further explore how gender and race predicted expectancy-value profile membership, we examined whether there were significant differences between the groups with regard to gender and race/ethnicity (see Table 8). For these analyses, we used logistic regression analyses in which race/ethnicity and gender were separately inputted as independent variables predicting the odds of being in one profile compared to another. The reported odds ratios are unadjusted for any covariates. For each pairing of profiles, the first reported profile was inputted as the base outcome.

Gender

Using men as the reference group, we found that the *High Math/High Science* profile had significantly fewer women than the *Low Math/Low Science* profile (OR = 0.55, SE = 0.08) and the *Moderate Math/Moderate Science* profile (OR = 0.63, SE = 0.06). An odds ratio of 0.55 implies that a woman was 45% less likely to be in the *High Math/High Science* profile compared to the *Low Math/Low Science* profile. The *Moderate Math/Moderate Science* profile (OR = 0.69, SE = 0.13) and *High Math/High Science* (OR = 0.43, SE = 0.08) profile were also comprised of significantly fewer women than the *High Math/Low Science* profile.

Race/Ethnicity

With regard to race/ethnicity and using White students as the reference group, the *High Math/Low Science* profile (OR = 2.48, SE = 0.73) and the *High Math/High Science* profile (OR = 1.78, SE = 0.39) had significantly more Asian students than the *Low Math/Low Science* profile. Asian students were disproportionately underrepresented in the *Low Math/High Science* profile compared to the *High Math/Low Science* profile (OR = 0.32, SE = 0.12). Both Asian students (OR = 2.21, SE = 0.81) and Black/African American students (OR = 2.26, SE = 0.82) were also disproportionately overrepresented in the *High Math/High Science* profile compared to the *Low Math/High Science* profile. Hispanic students were disproportionately underrepresented in the *High Math/High Science* profile compared to the *Low Math/Low Science* profile (OR = 0.53, SE = 0.12), the *High Math/Low Science* profile (OR = 0.45, SE = 0.11), and the *Moderate Math/Moderate Science* profile (OR = 0.66, SE = 0.12).

School Context

We also assessed school contextual factors, namely the degree to which high school teachers emphasized the enhancement of interest in math and science and percent of college-bound students were significantly associated with profile membership. We found small but significant differences between profiles by percent of college-going students: the *High Math/High Science* profile had a significantly higher percent of college-going students than the *Moderate Math/Moderate Science* profile (OR = 1.01, SE = 0.00) and the *Low Math/Low Science* profile (OR = 1.01, SE = 0.00). No other contextual variables were found to differentiate the frequency of students in profiles.

Outcomes Across Profiles

Table 4 displays STEM outcomes across the latent profiles. The *High Math/High Science* profile had the highest math GPA (M = 3.04, SD = 0.74), science GPA (M = 3.10, SD = 0.71), academic persistence rate (86% of profile), STEM major intentions in grade 12 (45% of profile), STEM major choice three years post-high school (48% of profile), and were the most likely to have STEM intentions in grade 12 and continue to be a STEM major three years later (40% of profile). Meanwhile, the *Low Math/Low Science* profile had the poorest outcomes, including lowest math GPA (M = 2.11, SD = 0.77), science GPA (M = 2.30, SD = 0.78), academic persistence rate (78% of profile), STEM intention in grade 12 (9% of profile), STEM major three years after high school (7% of profile), and were the least likely to continue to be a STEM major three years later if they had STEM intentions in grade 12 (5% of profile).

Math and Science GPA

Table 5 shows predictors of math GPA and science GPA using linear regression analyses with additional sociodemographic covariates. With the *High Math/High Science* profile as the reference group, all of the other profiles had significantly lower math GPA (βs = -.26 to -.88) and science GPA (βs = -.35 to -.75). Students also had significantly higher GPAs in math (βs = .20 to .25) and in science (βs = .13 to .21) if they had math teachers who placed moderate and heavy emphasis on increasing student interest in math, were women (βs = math: .23, science: .24), and had parents with increasing levels of education (βs = math: .19 to .28, science: .22 to .29). Meanwhile, math GPA and science GPA were significantly lower among students who were Black/African American (βs = math: -.51, science: -.50), Hispanic (βs = math: -.34, science: -.38), and from the lowest-income households (βs = math: -.23, science: -.25).

College and STEM Major Outcomes

Results of logistic regression predicting academic persistence, STEM major intentions, and STEM major choice are displayed in Table 6. Compared to the *High Math/High Science* profile, students in the *Low Math/High Science* profile (OR = 0.37, 95% CI = .21, .67) and *Moderate Math/Moderate Science* profile (OR = 0.69, 95% CI = .51, .92) had significantly lower odds of persisting in college three-years after high school graduation. All of the profiles had significantly lower odds of STEM major intentions (ORs = 0.13–.34) and STEM major choice (ORs = 0.10–.44) than the *High Math/High Science* profile.

Shifts from STEM Major Intentions to STEM Major Choice

Table 7 further displays predictors of student change in STEM major. First, we used logistic regression to predict whether students dropped STEM (i.e., intended to major in STEM at grade 12 but were not majoring in STEM three years later) compared to students whose STEM intentions remained (i.e., intended to major in STEM at grade 12 and were majoring in STEM three years later). Students in the *Low Math/Low Science* profile (OR = 4.13, 95% CI = 1.47, 11.54) and the *Moderate Math/Moderate Science* profile (OR = 2.00, 95% CI = 1.30, 3.07) were significantly more likely than the *High Math/High Science* profile to have dropped STEM as a major. Additionally, women were significantly more likely to drop STEM than men (OR = 1.77, 95% CI = 1.22, 2.56), while Asian students were less likely than White students (OR = 0.34, 95% CI = 0.24, 0.49). Students from middle-income households were significantly more likely to drop STEM as their major compared to the highest-income households (OR = 1.84, 95% CI = 1.11, 3.05).

Second, we predicted whether students added STEM (i.e., did not intend to major in STEM at grade 12 but were majoring in STEM three years later) compared to students whose STEM intentions remained (i.e., intended to major in STEM at grade 12 and were majoring in STEM three years later). We found no significant differences between the profiles compared to *High Math/High Science* as the reference group. Although, we did find that women were significantly more likely than men to add STEM (OR = 2.40, 95% CI = 1.70, 3.40) as were Black/African American students compared to White students (OR = 3.90, 95% CI = 2.07, 7.35). Meanwhile, students whose parents had a bachelor's degree (OR = .53, 95% CI = .35, .81) and master's degree (OR = .37, 95% CI = .24, .59) were significantly less likely to add STEM as a major compared to students whose parents had a high school diploma or less.

Differences in Outcomes Between Profiles

Table 9 displays differences in outcomes by pairs of each of the profiles. For these analyses, we conducted a series of linear and logistic regression analyses to predict the outcomes from the profiles. The profile pairings were inputted as independent variables with the outcomes as dependent variables. Given that math GPA and science GPA were continuous variables, analyses with these variables were conducted through linear regression analyses with Cohen's d as a standardized mean difference effect size. Analyses with academic persistence, STEM major intent, STEM major choice, and adding/dropping STEM as dependent variables were conducted through logistic regression analyses. The reported beta coefficients and odds ratios are unadjusted for any covariates; odds ratios also serve as effect sizes when converted to percentages of likelihood. For each pairing of profiles, the first reported profile was inputted as the reference group.

Math and Science GPA

With regard to math GPA and science GPA, significant differences emerged between nearly every pairing of profiles. Overall, profiles with higher levels of motivation in math and science outperformed profiles with lower levels of cross-domain motivation in math GPA and science in a monotonic fashion. In other words, the *High Math/High Science* had higher GPAs than the *Moderate Math/Moderate Science* profile (*βs* = math: .69, science: .63), which had higher GPAs than the *Low Math/Low Science* profile (*βs* = math: .48, science: .43). The exceptions included no significant difference in math GPA between the *Low Math/Low Science* and *Low Math/High Science* profiles; no difference in science GPA between the *High Math/Low Science* and *Low Math/High Science* profiles; no difference in math GPA or science GPA between the *High Math/Low Science* and *Moderate Math/Moderate Science* profiles; and no difference in science GPA between the *Low Math/High Science* and *Moderate Math/Moderate Science* profiles. In sum, profiles with higher levels of motivation outperformed profiles with lower levels of cross-domain motivation in math GPA and science GPA.

College and STEM Major Outcomes

Further differences emerged with regard to college outcomes and STEM major outcomes (see Table 9). For academic persistence, the *High Math/High Science* profile persisted at significantly higher rates than the *Low Math/High Science* (*OR* = 2.62), *Low Math/Low Science* (*OR* = 1.71), and *Moderate Math/Moderate Science* (*OR* = 1.59) profiles. For high school intent to choose a STEM major, once again the *High Math/High Science* profile was significantly more likely to indicate a STEM major intent than *Low Math/High Science* (*OR* = 3.04), *High Math/Low Science* (*OR* = 3.47), *Low Math/Low Science* (*OR* = 8.47), and *Moderate Math/Moderate Science* (*OR* = 3.41) profiles. Additionally, the *Low Math/Low Science* profile was significantly less likely to intend to major in STEM than the *Low Math/High Science* (*OR* = 2.79) and *Moderate Math/Moderate Science* (*OR* = 2.49) profiles. A similar pattern emerged for choosing a STEM major in college with the addition of the *High Math/Low Science* profile having significantly more students declare a STEM major compared to the *Low Math/Low Science* (*OR* = 3.16) profile. With regards to students changing their intent from a non-STEM major to choosing a STEM major, the *High Math/High Science* profile was less likely to add STEM compared to the Low Math/High Science profile (*OR* = .46) and Moderate Math/Moderate Science profile (*OR* = .57). There were also significant contrasts between the *Low Math/Low Science* with *High Math/Low Science* (*OR* = 0.40) and *Low Math/High Science* (*OR* = .47) profiles for dropping a STEM major after intending to study STEM upon high school graduation. In sum, profiles with higher levels of motivation outperformed profiles with lower levels of cross-domain motivation in STEM major intent (ORs = 2.44–8.47) and STEM major choice (ORs = 3.16–11.46). Moreover, the *High Math/High Science* profile had the highest levels of academic persistence through college (ORs = 1.59–2.62) and lower rates of changing their intent to major in a STEM field (ORs = .21–.47).

Discussion

In light of the increasing demand to enhance students' STEM educational and career-oriented trajectories, the current study sought to identify cross-domain profiles of math and science motivational beliefs among high school students and explore both their sociodemographic antecedents and academic and STEM-related outcomes linked with profile membership. Guided by expectancy-value theory, our findings revealed five distinct profiles of math and science expectancies and values. We also found that gender, race, and school context differentially predicted profile membership, which was also associated with a range of students' academic and STEM-related outcomes.

The Significance of Cross-Domain Motivation Profiles in Math and Science

To our knowledge, expectancies and values in math and science have not been examined together in cross-domain profiles until the current study. Overall, we found evidence for five profiles consisting of various intraindividual hierarchies of math and science motivation. Three of the five profiles reflected similar findings to prior studies examining task value profiles in math and science and other subjects (Chow et al., 2012). Namely, there were profiles that exhibited high, moderate, and low levels of motivation in both math and science. Representing the majority of the sample, these profiles were consistent with profile patterns found in prior studies (Lazarides et al., 2020; Simpkins & Davis-Kean, 2005). Most students were members of the *Moderate Math/Moderate Science* or *High Math/High Science* profiles. While this finding is encouraging, students may have endorsed relatively high levels of math and science motivation due to the restriction of our high school sample to students enrolling in some form of postsecondary education.

It should also be noted that across all five profiles, there was little differentiation of expectancies and value components within domains, i.e., high expectancy but low value, indicating that students had endorsed well-aligned expectancies and values in science and mathematics. Prior profile-based EVT studies have revealed profiles with differentiated expectancies and values (e.g., Perez et al., 2019; Watt et al., 2019), which illuminate the interactive elements of a high expectancy and low task value, or vice versa. However, this was not the case in the current study, in which student profiles were characterized by consistent levels of endorsement for both EVT components. Moreover, our results overall suggested that interactions of higher levels of expectancies and values resulted in better academic outcomes compared to interactions of lower expectancies and values. One possible explanation for our findings could be the high number of input variables in the profile analysis when combining science and math motivation variables together in the same LPA, which might limit the degree to which profile indicators can vary. A similar pattern was also reflected in Gaspard et al.'s (2019) study of motivation profiles for math and English. That being said, future research is needed to explore interactive differentiation of expectancy and value beliefs within cross-domain profiles.

Although relatively smaller in sample size, the other two profiles exhibited contrasting levels of math and science motivation, i.e., *High Science/Low Math* and *High Math/Low Science*. Given our interest in STEM-related outcomes, these findings shed light on the possible development of expectancies and values within some students who may have divergent motivations toward math and science. It challenges assumed practices that math and science motivational beliefs are to be measured as a single domain (Chow et al., 2011), or that they are to be assessed separately to create math-specific profiles and science-specific profiles (e.g., Simpkins & Davis-Kean, 2005). Cross-domain profiles allowed for the identification of a cluster of students who feel strongly motivated about math but not science, or vice-versa. The common understanding of STEM career pursuit resulting in joint motivation in math and science (Funk & Parker, 2018) and the importance of math and science for advanced STEM course-taking and course performance (Simpkins & Davis-Kean, 2005) favors the examination of students with proclivities toward both domains. However, our study sheds light on the profiles of students with differentiated motivations for math and science. Furthermore, based on the outcomes associated with profile membership, which we discuss in a subsequent section, we examined if profiles with stronger motivations toward math or with stronger motivations toward science fare better or worse to profiles with higher or more consistent levels of motivation in both domains simultaneously.

Outcomes Linked with Motivation Profiles

Profile membership was associated with a number of academic and STEM-related outcomes. Overall, profiles with higher levels of motivation in math and science outperformed profiles with lower levels of cross-domain motivation in math GPA, science GPA, STEM major intent, and STEM major choice. Moreover, the *High Math/High Science* had the highest levels of academic persistence through college and lower rates of changing their intent to major in a STEM field, supporting the importance of high levels of expectancies and values for undergraduates' decisions to persist or drop out (Schnettler et al., 2020). Altogether, reflecting moderate to large effect size differences, these findings highlight the benefit of having high to moderate levels of motivation for both math and science with the majority of the outcomes of interest, which are in line with other person-centered (e.g., Perez et al., 2019) and variable-centered research (e.g., Fong & Kremer, 2020).

Findings regarding the outcomes associated with profiles with differentiated motivations for math and science were mixed but mostly favorable. When compared to the *High Math/High Science* profile, the *Low Math/High Science* and *High Math/Low Science* profiles had lower math (*d*s = .34–.94) and science GPA (*d*s = .64) and lower rates of STEM major intent (26–35% less likely) and STEM major selection (23–30% less likely). Additionally, the *Low Math/High Science* had lower rates of academic persistence than the *High Math/High Science* profile (40% less likely). In contrast, although the results that students in the *Low Math/High Science* and *High Math/Low Science* profiles obtained a number of higher outcomes compared to those in the *Low Math/Low Science* profile were not too surprising, it was important to test whether students exhibiting differentiated hierarchies of motivation for science and math, on the whole, attained higher math and science achievement and endorsed greater STEM major intentions and choices as indicated by moderate to large effect size and odds ratio metrics. This finding suggests that having high motivation in either math or science is better than low motivation or at times moderate motivation in both these fields. Perhaps an intense enough interest or sense of competence in just one domain (math or science) can compensate for a lower motivation in the other domain.

What was more noteworthy, the outcomes for the two differentiated motivation profiles were nearly equivalent to those for the *Moderate Math/Moderate Science* profile. As an unexpected finding, compared to the *High Math/High Science* profile, the *Low Math/Low Science* and *Moderate Math/Moderate Science* profiles were more likely to drop their STEM major in college, but this was not the case for the *Low Math/High Science* and *High Math/Low Science* profiles. Although the differentiated motivation profiles seemed to do as well as the *Moderate Math/Moderate Science* profiles with regard to many of the outcomes, having high motivation in either math or science may serve as a buffer from changing one's intent to major in STEM and selecting a non-STEM major while in college. Thus, the relative placement of various tasks in an individual's hierarchy of expectancies and values toward math and science matters to a certain extent, presumably when comparing against students who are weakly motivated in both of these domains.

In sum, students with differentiated levels of motivation in math and science fared worse overall than those with high motivation in both domains, but maintenance of STEM major intentions from high school to college appeared to be consistent across all three groups. Moreover, these profiles had a higher likelihood of majoring in STEM than the *Low Math/Low Science* profile. One reason to explain this pattern of findings could be possible compensatory effects occurring for profiles with differentiated motivations toward science and math, so that high motivation in one of the domains compensates for lower motivation in the other. Altogether, differentiated hierarchies of motivation for these profiles may synergize together to attain outcomes tantamount to profiles of students with moderate levels of consistent motivation for math and for science.

Predictors of Motivation Profiles

In addition to identifying motivational profiles, we also examined if sociodemographic variables were associated with profile membership. In particular, we examined student characteristics of gender and race/ethnicity, in light of well-documented underrepresentation for women and people of color in the majority of STEM majors and careers (National Center for Science and Engineering Statistics, 2019). First, regarding gender, we found that among the profiles with consistent motivation toward math and science (i.e., *Low Math/Low Science*, *Moderate Math/Moderate Science*, *High Math/High Science*), women were disproportionately underrepresented in profiles in the *High Math/High Science* profile. This pattern of findings is aligned with prior studies (Wang & Degol, 2013) and also fits the alternative explanation that women tend to endorse higher levels of motivation than men in non-STEM domains such as English (e.g., Eccles et al., 1998). When compared with the *Moderate Math/Moderate Science* and *High Math/High Science*, women were more likely to be members of the *High Math/Low Science* profile. This pattern of findings points to another possible reason for the underrepresentation of women in STEM fields, in that, women might have strong motivation toward math but not toward science. We encourage future research to examine women with differentiated motivations in math and science and explore ways to support their STEM attainment as well as cultivating greater expectancy and value in both fields. One potential and popular approach to increase motivation at relatively low cost in STEM contexts may be to cultivate the utility value or relevance of science content in math courses and vice-versa (i.e., Harackiewicz et al., 2016).

Examining race/ethnicity as a predictor of profile membership, we also found disproportionate levels of particular racial/ethnic groups when contrasting pairs of profiles. With White students as the reference group, Hispanic students were underrepresented in the *High Math/High Science* profile compared to the *Moderate Math/Moderate Science* profile, *High Math/Low Science*, and the *Low Math/Low Science* profiles. One explanation for a lower representation of Hispanic students in high motivation profiles could be structural issues that might prevent Hispanic students and underrepresented minorities from cultivating motivation in math and science, such as diminished access to out-of-school STEM activities, advanced STEM courses in high school, and adequate mentoring (see Dawson, 2014; Guerra & Rezende, 2017; Safavian, 2019). When comparing the *Low Math/High Science* profile with the *High Math/High Science* profile, Black/African American students were more likely than White students to belong to the *High Math/High Science* profile. Although Black/African American students had greater representation in a more adaptive profile, perhaps they may have equivalent or at times higher levels of motivation toward math (Cokley, 2003), but other structural barriers may exist that prevent them attaining equivalent STEM performance and career outcomes. For instance, Black/African American students in STEM with higher interaction with faculty members were more likely to experience racial discrimination from professors (Park et al., 2020). We also encourage future research to consider race-reimaged (DeCuir-Gunby & Schutz, 2014; Matthews & Lopez, 2020) constructs of expectancies and task values for enhanced interpretative power to explain the role of culture- or race-specific motivations toward STEM subjects (see Matthews, 2018).

The only contextual variable that was associated with profile membership was the percentage of high school students going to college. Specifically, students in schools with a greater percentage of college-bound students were more likely to be in the *High Math/High Science* profile compared to the *Moderate Math/Moderate Science* profile and the *Low Math/Low Science* profile. This finding suggests that a college-going culture may be positively related to students exhibiting higher motivation for math and science. High schools with high college attendance tend to be wealthier with a greater number of resources (Jez, 2014), which can contribute to the promotion of advanced math- and science-related pursuits.

Contextual and Sociodemographic Predictors of Outcomes

In addition to the significant associations between profile membership and nearly all student outcomes, there were a number of contextual variables and sociodemographic variables that were significantly linked with student outcomes that are worth noting. A frequently overlooked aspect is the role of motivationally-supportive environments on students' motivational development and academic outcomes; therefore, in our study, we examined the role of teacher emphasis on increasing math interest and science interest as well as the percent of college-bound students as a proxy for a college-going school culture. We found that teachers' emphasis on increasing math interest (not for science interest) was positively associated with students' math and science GPA. Although the link between teachers' interest development in math and students' math grades was intuitive, the spillover effects of teacher-driven math interest to students' science grades was unexpected. To explain some of these results, we want to mention that there was little variance on both of these variables but more so with regard to teachers emphasizing science interest, with the vast majority of teachers indicating a heavy emphasis. Also, students' perceptions (rather than a teacher-report) of teachers' emphasis on math and science interest might be a more fruitful measure (see Schiefele & Schaffner, 2015). Social desirability bias may cause teachers to overestimate how much they try to emphasize interest in math and science to avoid reporting themselves as boring instructors; we expect students to provide a more accurate reporting of this kind of emphasis.

Furthermore, the school context variable of college-bound students positively predicted students' academic persistence in college, which supports the notion that the greater the number of high school peers enroll in postsecondary education, the more likely students are to persist in college overall. This finding is well-aligned with how a college-going school culture may motivate students not only to attend college but also to persist in college as well (Knight & Duncheon, 2020).

With regard to sociodemographic aspects, compared to men, women had higher GPA in math and science but lower rates of intending to major in STEM in high school and selecting STEM majors in college. This seemingly contradictory result has been supported by prior studies that suggest how women may outperform men in STEM-related courses yet do not major in STEM disciplines (Duckworth & Seligman, 2006). Contrary to many assumptions about gender differences, intellectual aptitude and academic performance are not main contributors to the underrepresentation of women in STEM compared to varying occupational preferences and work/family imbalance (Wang &

Degol, 2013). This pattern was also aligned with the overrepresentation of women in the *Low Math/Low Science* profile, suggesting that women may have alternative interests and motivations toward either verbal or more human-oriented (vs. task-oriented) domains. However, women did persist at higher rates while in college, which is consistent with prior research on gender differences and college attendance and academic persistence patterns (e.g., Kuh et al., 2008). Notably, women who intended to major in STEM also switched out from STEM at higher rates; conversely, women who did not intend to major in STEM later chose to major in STEM in college at higher rates. These seemingly diverging patterns point to the importance of postsecondary learning environments as contexts that can cause women to forgo their initial STEM major intentions or possibly switch from their original intent while in high school into a STEM major. We encourage future research to examine the high school to college transition for women with regard to STEM majors and the relevant supports that can either maintain or trigger STEM career paths for women.

Turning to the predictor of racial/ethnic group membership, we found that Black/African American students, Hispanic students, and students in the "Other" category had lower high school GPAs (with White students as the reference group). With regard to STEM major intentions and selection, some noteworthy patterns emerged. Compared to White students, Asian students were more likely to choose a STEM major and less likely to shift away from a STEM major from their intent in high school. Although Black/African American students on average had lower math and science GPAs, they were also more likely than White students to be in the *High Math/High Science* profile compared to the *Low Math/High Science* profile. Interestingly, this greater representation of Black/African American students in profiles higher in math motivational beliefs did not translate into higher intentions to major in STEM. One plausible explanation may be related to stereotype threat that harms both math performance (Steele & Aronson, 1995) and academic persistence in STEM fields (Beasley & Fisher, 2002). However, because they were more likely to add a STEM major while in college, this finding suggests the critical importance of the high school to college transition and potential opportunities for Black/African American students to enhance STEM-oriented motivation that may lead to switching into STEM majors.

Study Limitations

Despite the strengths of this study, it is not without its limitations. As with any longitudinal study, participants were lost due to sample attrition which may bias findings. Although we attempted to maximize the sample size through multiple imputation and utilized sampling weights to maintain the study sample's representative nature, we were unable to include all participants from the study's first wave. There are likely sociodemographic differences between participants who left the study which may have biased findings. For instance, there are disproportionately lower rates of college enrollment for men and Students of Color (National Center for Education Statistics, 2019) in the U.S. Thus, it would be beneficial for future scholars to examine STEM attainment and career pathways of the motivational profiles of students who do not enroll at postsecondary institutions within the first few years after high school graduation.

The present study is further limited by information collected by the original study authors. Because we used secondary data with instruments selected by other researchers, there are likely variables not included in the HSLS:09 which would have been valuable to the present study. Particularly, HSLS:09 did not include explicit measures of students' perceived cost regarding science and math, a component of expectancy-value theory that was omitted from our study. The HSLS:09 dataset contains a few items that assess how students perceive effort and time in mathematics and science takes them away from extracurricular activities, time with friends, being unpopular, and being made fun of. Although these items measure potential costs students pay for engaging in math and science, we did not think they adequately captured psychological cost, which may be a fruitful direction for latent profile research (see Gaspard et al., 2019; Perez et al., 2019). In addition, math intrinsic task value had a moderately low scale reliability. Perhaps students reported enjoyment in mathematics but may not have listed it as their favorite subject, particularly given a common perception that math is frequently thought of as a least favorite subject (i.e., Boaler, 2008). In addition, although we described the type of math and science courses students reported on when assessing their motivation, a finer-grained analysis comparing differences at the course level (i.e., honors, elective courses) could be a fruitful direction for future research.

We also want to acknowledge that our STEM major outcomes were limited to high school intent and college major selection variables. Collecting data on students' STEM-related degree and career attainment is a fruitful direction for future research to explore longer-term outcomes associated with profile membership. Moreover, our measure of students' retaining or changing their STEM major did not account for whether students actively chose to leave their major, which could be attributed to structural forces. We encourage additional research into if and why students leave STEM disciplines (see Rosenzweig et al., 2020). We also found limited evidence for contextual variables influencing profile membership among the data made available to us through the High School Longitudinal Study. Perhaps our measure of teachers' emphasis on cultivating math and science interest could be enhanced with a more robust measure (beyond a single item). Other variables such as teacher autonomy support, teacher-provided rationales to increase utility value, identity-based motivation interventions as well as instructor mindset (see Muenks et al., 2020) are potentially relevant predictors of profile membership.

Conclusion

Given the important role of student motivation in STEM education, our study revealed that although most students seemed to have consistent levels of motivation toward both math and science, there is a possibility for students' expectancy and value beliefs toward math to diverge from the same beliefs toward science. Theoretically, our results shed light on the process of intraindividual differentiation of expectancies and values for more closely related disciplines such as math and science. Lastly, we integrated in our study contextual factors that may support students' motivation such as teachers' interest enhancement and peers' college-going behaviors. Despite having little association with profile membership, contextual factors were linked with students' outcomes. We encourage additional scholarship that combines person-centered approaches and contextual determinants of students' motivation.

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Figure 1

Fit Statistics Across Latent Profiles

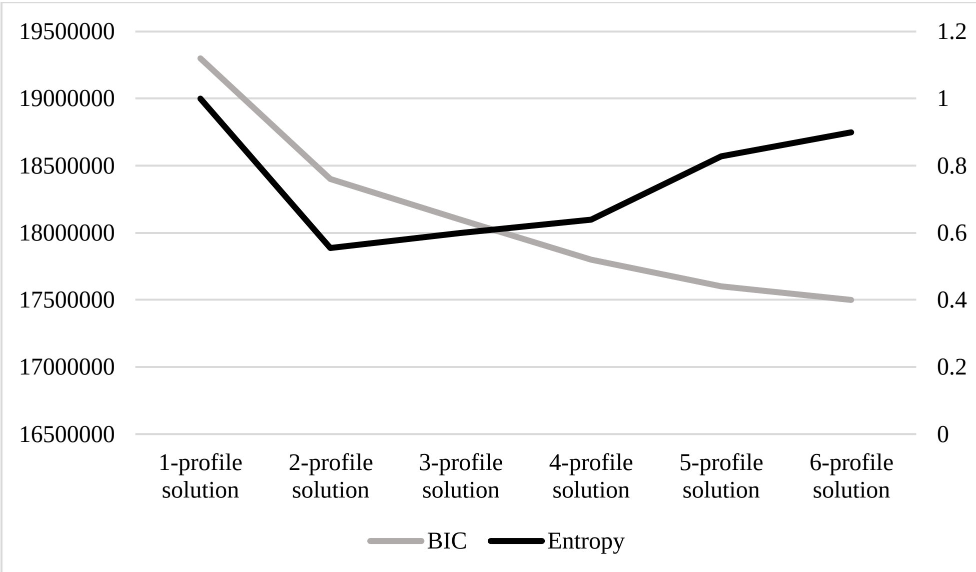

Figure 2

Indicators Across Latent Profiles

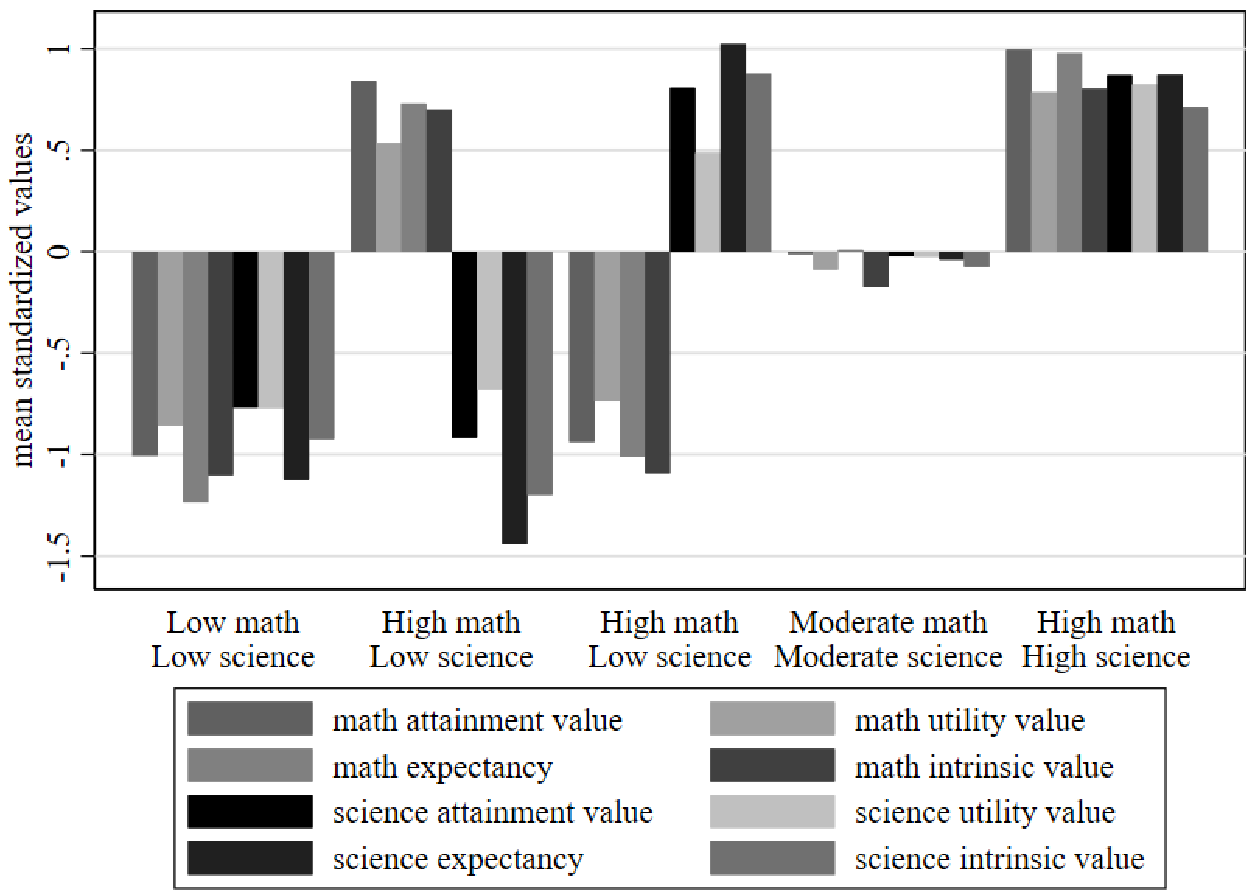

Table 1.

Pairwise Correlations Between Latent Indicators

	Math Attainment	Math Utility	Math Intrinsic	Math Expectancy	Science Attainment	Science Utility	Science Intrinsic
Math Attainment	1.00						
Math Utility	0.45***	1.00					
Math Intrinsic	0.63***	0.46***	1.00				
Math Expectancy	0.57***	0.38***	0.58***	1.00			
Science Attainment	0.27***	0.18***	0.16***	0.21***	1.00		
Science Utility	0.24***	0.44***	0.24***	0.23***	0.56***	1.00	
Science Intrinsic	0.13***	0.18***	0.21***	0.15***	0.57***	0.47***	1.00
Science Expectancy	0.18***	0.18***	0.14***	0.29***	0.49***	0.37***	0.57***

Note. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Table 2.

Latent Indicators Across Profiles

Variable	**Total Sample**	**Profile 1: Low math-Low science**	**Profile 2: High math-Low science**	**Profile 3: Low math-High science**	**Profile 4: Moderate math-Moderate science**	**Profile 5: High math-High science**
Math identity	0.16 (1.00)	-1.01 (0.69)	0.84 (0.74)	-0.94 (0.72)	-0.01 (0.77)	1.00 (0.71)
Math utility	0.08 (0.98)	-0.86 (1.01)	0.54 (0.79)	-0.74 (1.02)	-0.09 (0.83)	0.79 (0.60)
Math interest	-0.04 (0.99)	-1.10 (0.62)	0.70 (0.83)	-1.09 (0.60)	-0.18 (0.75)	0.80 (0.81)
Total math value	0.12 (0.99)	-1.31 (0.61)	0.75 (0.71)	-1.23 (0.61)	-0.21 (0.63)	0.96 (0.62)
Math expectancy	0.13 (0.97)	-1.23 (0.76)	0.73 (0.71)	-1.01 (0.79)	0.01 (0.59)	0.98 (0.65)
Science identity	0.15 (1.00)	-0.77 (0.83)	-0.92 (0.86)	0.81 (0.83)	-0.02 (0.78)	0.87 (0.83)
Science utility	0.13 (0.98)	-0.77 (1.00)	-0.68 (1.11)	0.49 (0.83)	-0.03 (0.78)	0.83 (0.72)
Science interest	0.05 (1.00)	-0.92 (0.84)	-1.20 (0.75)	0.88 (0.70)	-0.07 (0.79)	0.71 (0.79)
Total science value	0.09 (1.00)	-1.13 (0.79)	-1.27 (0.8)	0.74 (0.70)	-0.19 (0.69)	0.84 (0.71)
Science expectancy	0.09 (1.00)	-1.13 (0.79)	-1.44 (0.73)	1.02 (0.62)	-0.04 (0.63)	0.87 (0.70)
	N = 7,237	*n = 769 (10.63%)*	*n = 453 (6.26%)*	*n = 485 (6.70%)*	*n = 3,455 (47.74%)*	*n = 2,075 (28.67%)*

Note. Results of analyses of variance found each variable to be significantly different across profiles at $p < 0.001$. Standardized mean and deviations.

Table 3. *Socio-demographic Characteristics of Latent Profiles*

Variable	**Total Sample**	**Profile 1: Low math-Low science**	**Profile 2: High math-Low science**	**Profile 3: Low math-High science**	**Profile 4: Moderate math-Moderate science**	**Profile 5: High math-High science**
% higher education	78.25 (21.05)	77.23 (20.19)	78.73 (20.09)	78.47 (20.28)	77.63 (21.81)	80.15 (20.35)
Teacher emphasis on increasing math interest						
None or minimal	918 (12.69%)	120 (15.62%)	36 (7.87%)	67 (13.86%)	456 (13.20%)	239 (11.50%)
Moderate	3554 (49.12%)	359 (46.74%)	230 (50.76%)	248 (51.11%)	1704 (49.33%)	1008 (48.60%)
Heavy	2763 (38.19%)	289 (37.64%)	187 (41.37%)	165 (34.03%)	1295 (37.47%)	828 (39.90%)
Teacher emphasis on increasing science interest						
None or minimal	311 (4.30%)	22 (2.87%)	22 (4.79%)	35 (7.25%)	159 (4.60%)	73 (3.51%)
Moderate	3301 (45.62%)	390 (50.74%)	217 (47.92%)	205 (42.34%)	1569 (45.42%)	910 (43.87%)
Heavy	3625 (50.09%)	357 (46.38%)	214 (47.29%)	245 (50.42%)	1727 (49.99%)	1092 (52.62%)
Gender						
Male	3393 (46.89%)	319 (41.54%)	162 (35.68%)	228 (46.93%)	1545 (44.73%)	1168 (56.27%)
Female	3843 (53.11%)	450 (58.46%)	291 (64.32%)	257 (53.07%)	1910 (55.27%)	907 (43.73%)
Race						
White	4067 (56.21%)	419 (54.43%)	208 (45.88%)	303 (62.48%)	1932 (55.92%)	1221 (58.86%)
Asian	366 (5.06%)	24 (3.13%)	30 (6.66%)	14 (2.90%)	175 (5.06%)	125 (6.03%)
Black/African American	670 (9.26%)	56 (7.26%)	40 (8.93%)	27 (5.52%)	309 (8.95%)	243 (11.73%)
Hispanic	1507 (20.82%)	202 (26.30%)	119 (26.26%)	104 (21.40%)	750 (21.71%)	314 (15.11%)
Other	626 (8.65%)	68 (8.87%)	56 (12.38%)	37 (7.70%)	288 (8.34%)	172 (8.28%)
Parent education						
High school or less	2362 (32.64%)	304 (39.50%)	159 (35.18%)	162 (33.48%)	1156 (33.46%)	564 (27.18%)
Some college	1554 (21.47%)	167 (21.70%)	115 (25.38%)	77 (15.89%)	786 (22.76%)	401 (19.34%)
Bachelor's	1924 (26.59%)	181 (23.56%)	114 (25.27%)	159 (32.72%)	890 (25.76%)	587 (28.28%)
Master's or higher	1397 (19.30%)	117 (15.23%)	64 (14.17%)	87 (17.91%)	623 (18.02%)	523 (25.19%)
Income						
<$15,000	595 (8.22%)	99 (12.92%)	38 (8.39%)	35 (7.17%)	274 (7.94%)	142 (6.83%)
$15,000-$35,000	1218 (16.83%)	100 (13.05%)	93 (20.43%)	110 (22.67%)	566 (16.39%)	350 (16.87%)
$35,000-$55,000	1143 (15.80%)	157 (20.45%)	82 (18.17%)	56 (11.56%)	556 (16.09%)	282 (13.61%)
$55,000-$75,000	1018 (14.07%)	87 (11.31%)	47 (10.41%)	71 (14.62%)	519 (15.03%)	300 (14.46%)
$75,0001-$95,000	907 (12.54%)	104 (13.57%)	49 (10.84%)	61 (12.62%)	443 (12.81%)	250 (12.05%)
>$95,000	2355 (32.54%)	221 (28.69%)	99 (21.76%)	152 (31.36%)	1097 (31.74%)	751 (36.19%)
	N = 7,237	*n = 769 (10.63%)*	*n = 453 (6.26%)*	*n = 485 (6.70%)*	*n = 3,455 (47.74%)*	*n = 2,075 (28.67%)*

Table 4

STEM Outcomes Across Latent Profiles

Variable	Total Sample	Profile 1: Low math-Low science	Profile 2: High math-Low science	Profile 3: Low math-High science	Profile 4: Moderate math-Moderate science	Profile 5: High math-High science
Math GPA	2.65 (0.82)	2.11 (0.77)	2.76 (0.74)	2.29 (0.79)	2.59 (0.80)	3.04 (0.74)
Science GPA	2.76 (0.79)	2.30 (0.78)	2.58 (0.78)	2.62 (0.75)	2.73 (0.78)	3.10 (0.71)
College persistence						
No	1437 (19.86%)	171 (22.21%)	89 (19.60%)	147 (30.38%)	724 (20.96%)	296 (14.28%)
Yes	5799 (80.14%)	598 (77.79%)	364 (80.40%)	338 (69.62%)	2731 (79.04%)	1779 (85.72%)
STEM intention						
No	5477 (75.69%)	700 (91.03%)	365 (80.65%)	379 (78.22%)	2777 (80.37%)	1133 (54.60%)
Yes	1832 (25.32%)	69 (8.97%)	88 (19.35%)	106 (21.78%)	678 (19.63%)	942 (45.40%)
STEM major						
No	5328 (73.63%)	712 (92.64%)	362 (79.96%)	354 (73.02%)	2757 (79.80%)	1087 (52.39%)
Yes	1908 (26.37%)	57 (7.36%)	91 (20.04%)	131 (26.98%)	698 (20.20%)	988 (47.61%)
Change in STEM intention						
No change-not STEM major	4990 (68.96%)	682 (88.70%)	344 (75.99%)	336 (69.32%)	2599 (75.22%)	971 (46.78%)
No change-STEM major	1494 (20.64%)	39 (5.04%)	70 (15.38%)	88 (18.18%)	520 (15.05%)	826 (39.79%)
Dropped STEM	338 (4.67%)	30 (3.94%)	18 (3.97%)	17 (3.60%)	158 (4.58%)	116 (5.61%)
Added STEM	415 (5.73%)	18 (2.32%)	21 (4.66%)	43 (8.80%)	178 (5.15%)	162 (7.82%)
	N = 7,237	*n = 769 (10.63%)*	*n = 453 (6.26%)*	*n = 485 (6.70%)*	*n = 3,455 (47.74%)*	*n = 2,075 (28.67%)*

Table 5

Results of Regression Analyses Predicting Science GPA and Math GPA

Variables	Math GPA **β (95% CI)**	Science GPA **β (95% CI)**
Predicted class		
Low math-Low science	-0.88 (-0.96, -0.80)***	-0.75 (-0.85, -0.65)***
High math-Low science	-0.26 (-0.42, -0.10)**	-0.48 (-0.66, -0.31)***
Low math-High science	-0.76 (-0.86, -0.65)***	-0.48 (-0.61, -0.35)***
Moderate math-Moderate science	-0.43 (-0.49, -0.37)***	-0.35 (-0.42, -0.28)***
High math-High science	Reference	Reference
Math teacher emphasis on increasing math interest		
None or minimal	Reference	Reference
Moderate	0.20 (0.07, 0.32)**	0.13 (0.02, 0.24)*
Heavy	0.25 (0.11, 0.40)**	0.21 (0.10, 0.33)**
Science teacher emphasis on increasing science interest		
None or minimal	Reference	Reference
Moderate	0.02 (-0.16, 0.20)	0.03 (-0.14, 0.21)
Heavy	0.02 (-0.16, 0.20)	0.06 (-0.12, 0.24)
School % college-going	0.00 (-0.00, 0.00)	0.00 (-0.00, 0.00)
Gender – Female	0.23 (0.18, 0.29)***	0.24 (0.19, 0.30)***
Race		
White	Reference	Reference
Asian	0.03 (-0.14, 0.20)	0.07 (-0.02, 0.17)
Black/African American	-0.51 (-0.62, -0.39)***	-0.50 (-0.61, -0.38)***
Hispanic	-0.34 (-0.43, -0.24)***	-0.38 (-0.47, -0.29)***
Other	-0.30 (-0.41, -0.18)***	-0.33 (-0.44, -0.21)***
Income		
<$15,000	-0.23 (-0.38, -0.09)**	-0.25 (-0.39, -0.12)***
$15,000-$35,000	-0.12 (-0.25, -0.00)*	-0.14 (-0.28, 0.00)
$35,000-$55,000	-0.07 (-0.16, 0.02)	-0.07 (-0.15, 0.01)
$55,001-$75,000	-0.01 (-0.10, 0.08)	-0.03 (-0.10, 0.04)
$75,0001-$95,000	-0.01 (-0.09, 0.07)	-0.02 (-0.09, 0.06)
>$95,000	Reference	Reference
Parent education		
High school or less	Reference	Reference
Some college	0.01 (-0.08, 0.11)	0.02 (-0.10, 0.14)
Bachelor's	0.19 (0.11, 0.27)***	0.22 (0.14, 0.30)***
Master's or higher	0.28 (0.19, 0.36)***	0.29 (0.21, 0.38)***

Note. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Table 6

Results of Regression Analyses Predicting College Outcomes

Variables	**Persistence OR (95% CI)**	**STEM Intentions OR (95% CI)**	**STEM Major OR (95% CI)**
Predicted class			
Low math-Low science	0.68 (0.44, 1.05)	0.13 (0.08, 0.21)***	0.10 (0.06, 0.16)***
High math-Low science	0.77 (0.45, 1.32)	0.33 (0.21, 0.52)***	0.31 (0.20, 0.50)***
Low math-High science	0.37 (0.21, 0.67)**	0.34 (0.15, 0.74)**	0.44 (0.22, 0.87)*
Moderate math-Moderate science	0.69 (0.51, 0.92)*	0.31 (0.24, 0.39)***	0.30 (0.24, 0.36)***
High math-High science	Reference	Reference	Reference
Teacher emphasis on increasing math interest			
None or minimal	Reference	Reference	Reference
Moderate	0.88 (0.58, 1.33)	1.19 (0.75, 1.90)	1.09 (0.73, 1.60)
Heavy	0.97 (0.64, 1.46)	1.40 (0.88, 2.23)	1.23 (0.81, 1.85)
Teacher emphasis on increasing science interest			
None or minimal	Reference	Reference	Reference
Moderate	0.86 (0.41, 1.82)	0.97 (0.49, 1.93)	0.98 (0.50, 1.93)
Heavy	0.87 (0.41, 1.86)	0.82 (0.43, 1.58)	1.04 (0.52, 2.066)
School % college-going	1.01 (1.00, 1.01)**	1.00 (0.99, 1.01)	1.00 (1.00, 1.01)
Gender – Female	1.31 (1.05, 1.62)*	0.36 (0.28, 0.45)***	0.40 (0.32, 0.51)***
Race			
White	Reference	Reference	Reference
Asian	1.15 (0.66, 2.01)	1.53 (1.00, 2.34)*	2.12 (1.47, 3.05)***
Black/African American	0.82 (0.56, 1.20)	0.47 (0.28, 0.77)**	0.86 (0.57, 1.29)
Hispanic	0.73 (0.50, 1.09)	0.91 (0.62, 1.34)	0.94 (0.72, 1.24)
Other	0.65 (0.44, 0.96)*	1.00 (0.69, 1.44)	1.11 (0.81, 1.52)
Income			
<$15,000	0.74 (0.46, 1.17)	0.81 (0.51, 1.27)	0.76 (0.48, 1.18)
$15,000-$35,000	0.60 (0.43, 0.85)**	1.00 (0.62, 1.62)	0.92 (0.67, 1.25)
$35,000-$55,000	0.48 (0.33, 0.68)***	1.45 (1.05, 1.99)*	1.38 (1.05, 1.76)*
$55,001-$75,000	0.77 (0.55, 1.09)	1.26 (0.93, 1.70)	0.96 (0.74, 1.26)
$75,0001-$95,000	0.72 (0.51, 1.03)	1.23 (0.92, 1.64)	1.02 (0.77, 1.35)
>$95,000	Reference	Reference	Reference
Parent education			
High school or less	Reference	Reference	Reference
Some college	1.19 (0.77, 1.84)	1.09 (0.73, 1.64)	1.04 (0.68, 1.58)
Bachelor's	2.07 (1.47, 2.90)***	1.61 (1.19, 2.18)**	1.45 (1.10, 1.92)**
Master's or higher	2.01 (1.41, 2.87)***	1.66 (1.23, 2.25)**	1.44 (1.06, 1.97)*

Note. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Table 7

Change in STEM Major from Grade 12 to Three Years Post-High School Graduation

Variable	**Model 1: Dropped STEM OR (95% CI)**	**Model 2: Added STEM OR (95% CI)**
Predicted class		
Low math-Low science	4.13 (1.47, 11.54)**	1.61 (0.50, 5.18)
High math-Low science	1.34 (0.56, 3.20)	1.54 (0.62, 3.82)
Low math-High science	2.12 (0.97, 4.66)	2.01 (1.12, 3.59)
Moderate math-Moderate science	2.00 (1.30, 3.07)**	1.71 (1.12, 2.63)
High math-High science	Reference	Reference
Teacher emphasis on increasing math interest		
None or minimal	0.77 (0.41, 1.44)	0.72 (0.34, 1.75)
Moderate	0.88 (0.44, 1.72)	0.74 (0.33, 1.98)
Heavy		
Teacher emphasis on increasing science interest		
None or minimal	Reference	Reference
Moderate	0.89 (0.30, 2.66)	0.67 (0.29, 1.56)
Heavy	0.63 (0.21, 1.87)	1.07 (0.45, 2.27)
School % college-going	0.99 (0.98, 1.00)**	0.99 (0.99, 1.00)
Gender – Female	1.77 (1.22, 2.56)**	2.40 (1.70, 3.40)***
Race		
White	Reference	Reference
Asian	0.34 (0.24, 0.49)*	1.45 (0.68, 3.13)
Black/African American	1.09 (0.55, 2.13)	3.90 (2.07, 7.35)**
Hispanic	0.55 (0.28, 1.08)	0.62 (0.35, 1.10)
Other	0.72 (0.38, 1.37)	1.26 (0.79, 2.00)
Income		
<$15,000	0.93 (0.44, 1.97)	0.99 (0.38, 2.07)
$15,000-$35,000	3.30 (1.80, 6.04)**	1.53 (0.69, 2.47)
$35,000-$55,000	1.44 (0.90, 2.30)	1.02 (0.54, 1.53)
$55,001-$75,000	1.84 (1.11, 3.05)*	0.61 (0.34, 1.08)
$75,0001-$95,000	1.05 (0.68, 2.30)	0.61 (0.40, 0.93)
>$95,000	Reference	Reference
Parent education		
High school or less	Reference	Reference
Some college	0.72 (0.42, 1.21)	0.67 (0.42, 1.07)
Bachelor's	0.77 (0.49, 1.22)	0.53 (0.35, 0.81)*
Master's or higher	0.60 (0.34, 1.04)	0.37 (0.24, 0.59)**

Note. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Table 8

Covariates Predicting Latent Profile Membership

Variables	Low Math-Low Science vs High Math-Low Science OR(SE)	Low Math-Low Science vs Low Math-High Science OR(SE)	Low Math-Low Science vs Mod Math-Mod Science OR(SE)	Low Math-Low Science vs High Math-High Science OR(SE)	High Math-Low Science vs Low Math-High Science OR(SE)	High Math-Low Science vs Mod Math-Mod Science OR(SE)	High Math-Low Science vs High Math-High Science OR(SE)	Low Math-High Science vs Mod Math-Mod Science OR(SE)	Low Math-High Science vs High Math-High Science OR(SE)	Mod Math-Mod Science vs High Math-High Science OR(SE)
Gender										
Male	Reference	Reference	Reference	Reference	Reference	Reference	Reference	Reference	Reference	Reference
Female	1.28(0.29)	0.80(0.20)	0.88(0.14)	0.55(0.08)***	0.63(0.21)	0.69(0.13)*	0.43(0.08)***	1.08(0.29)	0.69(0.18)	0.63(0.06)***
Race										
White	Reference	Reference	Reference	Reference	Reference	Reference	Reference	Reference	Reference	Reference
Asian	2.48(0.73)**	0.80(0.26)	1.57(0.41)	1.78(0.39)**	0.32(0.12)*	0.63(0.20)	0.72(0.22)	1.95(0.73)	2.21(0.81)*	1.13(0.19)
Black/AA	1.46(0.63)	0.66(0.30)	1.20(0.53)	1.49(0.71)	0.45(0.19)	0.82(0.27)	1.02(0.40)	1.81(0.68)	2.26(0.82)*	1.24(0.29)
Hispanic	1.18(0.24)	0.71(0.36)	0.80(0.16)	0.53(0.12)**	0.60(0.26)	0.68(0.15)	0.45(0.11)**	1.13(0.48)	0.75(0.33)	0.66(0.12)*
Other	1.66(0.93)	0.76(0.19)	0.92(0.20)	0.88(0.21)	0.46(0.28)	0.55(0.33)	0.52(0.32)	1.21(0.29)	1.14(0.27)	0.94(0.13)

Note. Unadjusted odds ratios, for each paired comparison first group represents the baseline group; AA = African American; *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Table 9. Latent profiles predicting outcomes

	Low Math-Low Science vs High Math-Low Science	Low Math-Low Science vs Low Math-High Science	Low Math-Low Science vs Mod Math-Mod Science	Low Math-Low Science vs High Math-High Science	High Math-Low Science vs Low Math-High Science	High Math-Low Science vs Mod Math-Mod Science	High Math-Low Science vs High Math-High Science	Low Math-High Science vs Mod Math-Mod Science	Low Math-High Science vs High Math-High Science	Mod Math-Mod Science vs High Math-High Science
Outcomes	β (SE)	β (SE)	β (SE)	β (SE)	β (SE)	β (SE)	β (SE)	β (SE)	β (SE)	β (SE)
Math GPA	0.65(0.10)***	0.18(0.10)	0.48(0.05)***	0.93(0.05)***	-0.82(0.15)***	-0.25(0.13)	0.46(0.14)**	0.45(0.13)***	1.15(0.14)***	0.69(0.05)***
Cohen's d	0.79	0.23	0.61	1.23	1.07	0.22	0.38	.38	0.98	0.58
Science GPA	0.28(0.12)*	0.32(0.12)**	0.43(0.05)***	0.80(0.05)***	0.06(0.10)	0.23(0.15)	0.85(0.16)***	0.17(0.16)	0.77(0.16)***	0.63(0.07)***
Cohen's d	0.36	0.42	0.55	1.07	0.05	0.19	0.70	0.14	0.66	0.50
Outcomes	OR (SE)	OR(SE)	OR(SE)	OR(SE)	OR(SE)	OR(SE)	OR(SE)	OR(SE)	OR(SE)	OR(SE)
Persistence	1.17(0.35)	0.65(0.21)	1.08(0.21)	1.71(0.37)*	0.56(0.24)	0.92(0.23)	1.46(0.36)	1.56(0.47)	2.62(0.94)*	1.59(0.22)**
STEM intent	2.44(0.74)**	2.79(1.10)*	2.49(0.69)**	8.47(2.23)***	1.14 (0.53)***	1.02(0.23)	3.47 (0.74)***	0.89(0.38)	3.04(1.25)**	3.41(0.36)***
STEM major	3.16(0.78)***	4.66(1.57)***	3.19(0.78)***	11.46(2.84)***	1.48 (0.66)***	1.01(0.23)	3.63 (0.80)***	0.69(0.26)	2.46(0.88)*	3.59(0.34)***
Dropped STEM	0.40(0.13)**	0.47(0.15)*	0.44(0.22)	0.21(0.09)***	1.17 (0.47)	1.09(0.47)	0.51 (0.23)	0.93(0.39)	0.44(0.15)*	0.47(0.11)**
Added STEM	0.94(0.25)	1.12(0.33)	0.91(0.37)	0.51(0.28)	1.19 (0.34)	0.97(0.50)	0.55 (0.29)	0.81(0.25)	0.46(0.14)*	0.57(0.14)*

Note: Unadjusted beta coefficients and odds ratios, for each paired comparison first group represents the baseline group; *p<0.05, **p<0.01, ***p<0.001