Factors Impacting Advanced Math Course-Taking: A Multilevel Modeling Analysis of the HSLS:09

Shelby Gayle Roberts

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FACTORS IMPACTING ADVANCED MATH COURSE-TAKING: A MULTILEVEL MODELING ANALYSIS OF THE HSLS:09

by

Shelby Gayle Nabors Roberts

A Dissertation
Submitted in Partial Fulfillment of the
Requirements of the Degree of
Doctor of Philosophy

Major: Educational Psychology and Research

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May 2022
Dedication

I dedicate my dissertation work to my two children who have inspired me and encouraged me throughout graduate school and writing. They both have sacrificed many moments of their childhood to allow me to pursue my passions. Their love, admiration, and constant queries about “when will you finish Mom?” have pushed me through to the finish line. I love and cherish you both.
First and foremost, I want to acknowledge my loving partner, Drew, for his constant and never-ending support. Completing my dissertation during a global pandemic was not easy but was made possible by your steadfast faith in my ability to do this work. You encouraged me to not give up in my darker moments and continually reminded me of my “why.” I would not have been able to complete this journey over the last five years without you. I look forward to our next adventures that don’t revolve around deadlines and writing.

Next, I would like to thank my dissertation committee for your time, effort, thoughtful feedback, and continued support. I want to thank Dr. Xu for your support and advice throughout this process. Your feedback throughout my entire program has made me a better writer and scholar. Without your hard deadlines, I don’t know if I would ever have submitted that first draft. Dr. Leigh Harrell-Williams, your mentorship in navigating research, school, work, and family kept me balanced and focused on what matters most. Thank you for answering frantic emails and always reminding me that no results are in fact results and very much have a place in academia and research. Dr. Karen Kitchens, your feedback on my dissertation was invaluable and working with you teaching statistics during a pandemic was never dull. Dr. Mueller, thank you for introducing me to the SEVT framework which has shaped my research and encouraging me throughout this process.

Finally, I would like to thank the amazing women also pursuing their doctorates in the Department of Counseling, Educational Psychology and Research at the University of Memphis. Your mentorship, friendship, and scholarship have made me a better researcher and I will always cherish the relationships we made on this journey.
Abstract

The United States continues to lag other first-world countries in the number of students prepared to enter the STEM workforce. Research has shown that taking advanced math courses during high school better prepares students to enter college STEM programs (Byun et al., 2015; Chen, 2016). Both student and school characteristics often shape which courses students take in secondary school. Previous academic achievement and performance along with motivational factors, like expectations, math identity and self-efficacy, and students’ valuation of mathematics work concomitantly to shape students’ math course enrollments in high school (Attewell & Domina, 2008; Burkman & Lee, 2003; Maltese & Tia, 2011). Often remiss from the research are school impacts, like location, SES, and sector, which can impact course opportunities for students (Oakes & Saunders, 2004; Tyson et al., 2007; Xu & Kelly, 2020).

For this study, a sample of 2,826 students from 778 United States high schools was drawn from the High School Longitudinal Study of 2009. Students were evenly split between three racial/ethnic groups, Hispanic/Latinx, White, and Black, and results were analyzed separately for each group. Grounded in Situated Expectancy Value Theory, this study utilized multilevel regression modeling to examine the personal and school-level characteristics that impacted the highest math course taken during high school. Through a hierarchical model-building approach, these factors for each racial group were examined. Results revealed that for Black students, school-level characteristics were not influential, whereas for White and Hispanic/Latinx students school location and sector were impactful. For student-level characteristics, math ability was significant across all racial/ethnic groups and eighth-grade math grade and identity were significant only for some students. Findings from this study highlight the
importance of a strong foundation in math to prepare students to enter STEM fields. This study provides practical implications for teachers, parents, students, and policymakers.

*Keywords: SEVT, values, choice, mathematics course-taking, high school, racial differences, school characteristics*
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Chapter 1: Introduction

The need for STEM professionals has drastically increased in recent years and projections by human resources professionals state that by 2025 nearly 3.5 million STEM jobs will need to be filled (Lazio & Ford, Jr., 2019). Since 1990, employment in STEM fields has grown 79% and will continue to grow by at least 8% in the next ten years (Funk & Parker, 2018; National Science Board, 2020; Zilberman & Ice, 2021). In 2018, the Committee on STEM Education of the National Science & Technology Council set a vision that all Americans will have high-quality STEM education and strive to be a global leader in STEM literacy, innovation, and employment to meet the booming need for STEM workers. One of their three primary goals to achieve this vision is to “increase diversity, equity, and inclusion in STEM and provide all Americans with lifelong access to high-quality STEM education, especially those historically underserved and underrepresented in STEM fields and employment” (2018, p. v). The current landscape in STEM education is a far cry from equitable or accessible, though the need for and vision to achieve equitable high-quality STEM education to all people in the U.S. are evident.

Trends in STEM Education

The need for a robust STEM workforce cannot be understated in today’s global economy. The United States is often lagging behind in producing the number of well-trained STEM professionals that the workforce demands (National Science Board, 2010, 2012). The 2018 Program for International Student Assessment (PISA), which focused on mathematics, found that mathematics assessment results for 15-year-olds in the United States fell in the bottom half of all Organization for Economic Co-operation and Development (OECD) member nations (OECD, 2019). This finding paints a grim picture of how prepared our students are pursuing STEM careers as they enter college and the workforce. The majority of STEM college graduates
and graduate students in STEM programs are not coming from U.S. high schools (Herman, 2019), likely because U.S. high school students are underprepared to pursue STEM college majors (Snyder et al., 2016).

Extant literature suggests that disparities in STEM preparation remain commonplace. Originally, the focus of STEM disparities was on gender gaps (e.g., Leslie et al., 1998). Gender gaps in degrees still remain in the more computational STEM fields, e.g., math, computer science, engineering, but have sharply narrowed if not closed over the last decade in STEM fields in general (Funk & Parker, 2018; Tyson et al., 2007). Now, we must turn to the imbalance in STEM based on racial or ethnic backgrounds. In 2016–2017 just over half of all STEM degrees were awarded to White students (58%), while Latinx/Hispanic students received the second-largest proportion at 17% (American Association of Community Colleges, 2019). The National Science Board (NBS; 2021) found that White and Asian students outscored their Black, Latinx/Hispanic, Indigenous American, and Pacific Islander peers by over 10% and that students from low-SES backgrounds scores 30-points lower than high-SES students even controlling other factors (Rotermund & Burke, 2021). These continued disparities in STEM education in the U.S. have led countless organizations to include diversity or equity as prominent features in their visions, missions, and goals. For example, the NSB in partnership with the National Science Foundation (NSF) wants to “ensure that NSF improves the attractiveness, equity, and inclusivity of research careers, including attracting and retaining women and other underrepresented groups” (NSB, 2020). Additionally, equity is one of the three main goals outlined by the National Science and Technology Council (Committee on STEM Education, 2018).
**Statement of the Problem**

The U.S. must “plug” leaks and fill cracks in the STEM pipeline in order to produce the vast STEM workforce that is needed. Imagining a straight continuous pipe from elementary to a STEM career is overly simplistic and not a true representation of STEM trajectories (Cannady et al., 2014). Instead, we must envision a complex network of pipes that enter and exit at various points, but the matrix of pipes still leads to a STEM career. When we think of the pipeline as a complex latticework, it allows us to see that there will be normal entry and exit points along the way. However, losing students at unplanned or unexplained points shows that there are still leaks and cracks in the pipeline that we must aim to alleviate (Ferebee et al., 2019).

One of these leaks can occur in high school or just prior in the eighth grade. That leak is due to not taking rigorous math courses even when students are eligible to do so. Students who take Algebra I earlier in K–12, either in eighth or ninth grade, have a better chance of completing higher-level math courses in high school, which in turn allows them to be better prepared for college STEM majors (Holian & Kelly, 2020; USDOE, 2018). The lack of rigorous math courses in high school leads to many students being underprepared for college. ACT (2018) found that only 20% of U.S. graduates met the ACT STEM Readiness Benchmark. More telling is that students who are underserved, i.e., minority, low-SES, or first-generation students, fall even further behind. Only 10% of students who met a single underserved criterion met STEM benchmarks compared to 29% of students who were not a member of any of the underserved groups. Additionally, STEM intenders or newcomers, defined as those who intended to hold a STEM career by age 30 at the beginning or end of high school, took a larger proportion of credits in precalculus, calculus, or physics compared to STEM leavers and non-intenders, defined as those who by 12th grade no longer or never sought to work in a STEM field. This relationship
means that students are more likely to take higher math courses and thus be better prepared for STEM in college if a student is interested in a career in STEM by the end of high school.

Research is needed to understand the nature of the various factors that play into STEM credit attainment and, more specifically, rigorous math course completion during high school. In the past, research often grouped all high school students together and measured impacts including those related to race or ethnicity. It is evident that racial and cultural norms interact with students’ beliefs, goals, and ideals differently. Research has begun to examine some of the factors separately for different racial/ethnic groups (e.g., Anderson & Ward, 2013; Safavian, 2019), but more work is needed to fully understand how various groups of students make course-taking choices in high school that will influence their educational and career trajectory for many years.

**Purpose of the Study**

The purpose of this study was to examine how background characteristics, motivational factors, and school-level environments work to impact the highest-level mathematics courses students take during high school. Guided by Eccles, Wigfield, and colleagues’ (1983, 2020) theoretical perspectives of achievement and choice in education, this study utilized multilevel regression to examine how background characteristics, motivational factors, and school-level environments work to impact the highest-level mathematics courses students take during high school. Results from this study provide both practical implications for K-12 educators and policymakers as well as implications for future research and large-scale NCES studies.
Chapter 2: Literature Review

The purpose of this section is to review the most notable research on high school STEM achievement and the factors that influence it. The review begins with an investigation of the analytic framework that will be used in this proposed study. Following this, a review of literature of the associated factors is conducted, first by discussing math course enrollment in high school and specifically the importance of this factor for future STEM degree attainment. Following this, the review will move to the factors that impact STEM achievement-related choices and performance at both the student and school levels.

**Situated Expectancy-Value Theory**

Situated Expectancy-Value Theory (SEVT) is a popular framework for examining and estimating how students make specific educational choices like achieving and persisting in academic-related endeavors. Various motivational theories have come from many different intellectual traditions, though modern motivational theories tend to focus “on the relation of beliefs, values, and goals with action” (Eccles & Wigfield, 2002, p. 100; Weiner, 1992). The study of motivation in psychology has often included the constructs of expectancy and value and how those influence individual’s actions, but when looking at actions in the school context both motivational factors and social cognitive factors come into play (Wigfield et al., 2016). Eccles-Parsons and colleagues (1983) originally coined the term Expectancy-Value Theory (EVT) by building off Atkinson’s Theory of Motivation (1977) and Bandura’s Social Cognitive Theory (1977) in order to explain why there are gender differences in achievement choices, specifically the factors that led girls and young women to and away from STEM fields. SEVT has a long history in studies related to STEM achievement and attainment and is considered as one of the appropriate frameworks for investigating how motivational factors impact advanced math
course-taking during high school as supported by the evidence presented in the following sections.

SEVT consists of numerous exogenous factors that work concomitantly to impact an individual’s expectations, values, and ultimately achievement. That future achievement then serves as past experiences which will impact educational motivations even further off, thus creating the cyclical nature of the SEVT framework as depicted in Figure 1. The following sections outline the various components of the Situated Expectancy-Value Theory and provide the groundwork for the variables considered in this study. Many of these concepts overlap with other motivational, achievement, and social-cognitive theories, so Table 1 is provided to outline the similarities and differences.

![Situated Expectancy-Value Theory of Achievement Performance and Choice (Eccles & Wigfield, 2020)](image)

**Figure 1**

*Situated Expectancy-Value Theory of Achievement Performance and Choice (Eccles & Wigfield, 2020)*
Goals and General Self-Schemata

**Self-Concept of Ability Beliefs.** Expectancies and ability beliefs relate to the cognitive process of making judgments about ‘am I able to do this task.’ Ability beliefs are “the individual’s perception of his or her current competence at a given activity” (Wigfield & Eccles, 2000, p. 70), while self-judgment about how well one will do on an upcoming task is expectancy. The primary difference between the two is that ability-beliefs are in the present and expectancies ask the student to make judgments about the future (Wigfield & Eccles, 2000). These self-perceptions are influenced by short- and long-term goals, self-schemas or identities, and self-concepts.

Academic self-concepts are closely tied to self-efficacy from Bandura’s (1977) Social-Cognitive Theory (SCT) and ask the student to make judgments about their own ability in the present situation (Wigfield & Eccles, 2000). In line with self-efficacy, ability beliefs in SEVT ask students about their own expectations for success which is different from outcome expectations which assess if a task/action will lead to a specific outcome. These ability beliefs are domain-specific instead of task-specific like in SCT.

A student’s belief in their success in math can be very different from their belief in their success in sports (domain-specific) but is not as task-specific as to ask their beliefs about calculating an acute angle in a math course. In the past, academic self-concepts and expectancies were closely tied and often modeled together as a single construct (e.g., Eccles et al., 1993; Eccles & Wigfield, 1995), though in reality they are separate constructs and should be modeled as such (Eccles & Wigfield, 2020).

**Self-Schemata.** Self-schemas “reflect individuals’ beliefs and self-concepts about themselves” and what they believe they can become and who they currently are (Schunk et al.,
2014, p. 54). When an individual processes information related to the self and the way they have behaved in the past, they form their self-schemata. “Self-schemata can be viewed as a reflection of the invariances people have discovered in their own social behavior. They represent patterns of behavior that have been observed repeatedly…” (Markus, 1977, p. 64). The self-schema concept posits that the individual has organized their past behaviors into categories and can discern patterns in their own behavior which in turn predicts future decisions and performance.

**Personal and Social Identities.** This factor was previously comprised in the self-schema portion of the SEVT model, though were later separated into a unique factor under the Goals and Self-Schemata construct (Eccles & Wigfield, 2020). Social identity is “that part of the individual’s self-concept which derives from his or her knowledge of membership to a social group (or groups) together with the value and the emotional significance attached to it” (Tajfel, 1981, p. 255). A person can have many social identities where some overlap or take precedence over others. The conglomeration of social identities feed into one’s overall self-concept (Amiot, 2007). Personal identities on the other hand are a person’s self-categorization or identification of their previous responses and experiences not necessarily in relation to social groups, but to the world around them in general. These personal and social identities ask one to view and categorize their previous behaviors and thus allowing them to make future predictions about how they will perform or engage with new things. If a student views themselves as a math person, they will likely be motivated to engage in tasks and perform in ways that reinforce that identity.

**Short- and Long-Term Goals.** Additionally, under this larger construct are goals, which are defined as cognitive depictions of what one hopes to accomplish. They can be short- or long-term and concrete or abstract. Derived from motives-as-goals (Elliott & Dweck, 1988), goals entice individuals to action. Goals give “meaning, direction, and purpose” to the actions and
dictate the intensity and quality of the actions as goals are adjusted and redefined (Covington, 2000). For example, a high schooler may have a short-term goal of passing sophomore chemistry and a related, but a long-term goal, of majoring in college chemistry. These goals are influenced by past performance, socialization, and academic self-concepts.

**Affective Memories and Experiences**

Affective memories are the emotions related to past learning activities and experiences (Gorges & Kandler, 2012). It was originally called affective experiences in Eccles’s first model (1983) but was later changed to incorporate both the experiences and the memories of the feelings themselves. It is now viewed as a single factor that is influenced by social agents and an individual’s interpretation of their own experiences (Wigfield & Eccles, 2000). Some have viewed this construct as a “less rational process in motivating behavioral choices” since a person’s emotions about a previous experience are not always logical or understandable (Eccles & Wigfield, 2005, p. 122). Of all the concepts in the SEVT model, this one has received the least empirical investigation (Gorges & Kandler, 2012). Regardless though, it can impact how an individual will engage with and value future achievement-related tasks and thus is a viable antecedent for subject task values as evidenced by the small effect Gorges and Kandler (2012) found in their work.
Table 1

Construct Overlap Between Motivational Theories

<table>
<thead>
<tr>
<th>SEVT Construct</th>
<th>Other Theories and Their Similarities and Differences</th>
</tr>
</thead>
</table>
| Expectancies for Success (ESs) | **Self-Efficacy Theory** (Bandura, 1977)  
Bandura had two constructs that are often linked to SEVT’s ESs. ESs are more similar to his efficacy expectations construct than they are the outcome expectations. ESs measure the “individuals’ own expectation for success rather than their outcome expectation” (Wigfield & Eccles, 2000, p. 71).  
**Social Cognitive Theory** (Bandura, 1986; Schunk & DiBenedetto, 2020) & **Social Cognitive Career Theory** (SCCT) (Lent at al., 1994)  
SCCT also separates out self-efficacy and outcome expectations, so its view of self-efficacy, beliefs about one’s ability to perform particular behaviors, would align more with SEVTs ESs. However, like Bandura they view these as more task specific than domain specific. |
| Self-Concept of One’s Abilities or Ability Beliefs | **Attribution Theory** (Weiner, 1985)  
Ability beliefs are viewed by individuals as stable characteristics with little ability for growth. Contrary to SEVT, these are often seen as over-arching ability and not as specified as in SEVT.  
**Self-Concept Theories** (SCT) (Harter, 1990; Marsh 1989)  
In (SCT) ability beliefs are similar in that they are domain specific, and both have external (peer) and internal influences.  
**Self-Efficacy Theory**  
In SET ability is measured at the task specific level not the domain level. Additionally, they ask about a person’s confidence in their ability to complete a task and not in the ability in comparison to others.  
**Dimensional Comparison Theory** (Moller & Marsh, 2013)  
In dimensional comparison theory an individual is comparing their ability in one domain to make judgements about their ability in another domain. approach differs from SEVT in those comparisons in SEVT are self to others on a single domain and not self to self on various domains. |
| Goals | **Self-Concept Theory**  
Choice goals in SCCT are an outcome of self-efficacy, expectancies, and interests not a precursor to expectancies.  
**Achievement Goal Theory** (Dweck, 1986; Nicholls, 1984)  
Similar to goal theory, goals in SEVT have both individual and broad contexts for their formation. However, they conceptualize goals into mastery/learning and performance goals. |
<table>
<thead>
<tr>
<th>SEVT Construct</th>
<th>Other Theories and Their Similarities and Differences</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Identity</strong></td>
<td>Self-Schema &amp; Self-Concept Theories (Markus &amp; Wurf, 1987)</td>
</tr>
<tr>
<td></td>
<td>Here they refer to self-concept as identity, in contract to self-concept of ability as discussed earlier. They highlight the importance of multidimensionality of a person’s identity and reference the “working self-concept” as the active, shifting self-knowledge. Self-concept theorists have a much richer definition of identity than is used in the SEVT model, though they do not necessarily run contrary to one another.</td>
</tr>
<tr>
<td><strong>Interest or Intrinsic Value</strong></td>
<td>Self-Determination Theory (SDT) (Ryna &amp; Deci, 2020)</td>
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<tr>
<td></td>
<td>It is similar to the intrinsic motivation construct in self-determination theory because it speaks about doing a task out of the sheer enjoyment of the task.</td>
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<tr>
<td></td>
<td>Interest Theories (Alexander et al., 1994; Hidi &amp; Harackiewicz, 2001)</td>
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<td>In these theories individual interest is separated from situational interest; the latter being an emotional state, though the former is a “relatively stable evaluative orientation toward certain domains” (Eccles, 2002, p. 114). The individual interest has two components, feeling related and value related. The second is most similar to how SEVT views interest.</td>
</tr>
<tr>
<td><strong>Utility Value</strong></td>
<td>Self-Determination Theory</td>
</tr>
<tr>
<td></td>
<td>SEVT’s utility value is similar to extrinsic motivation in that it can be a means to an end. However, different from extrinsic motivation it can also relate to certain goals one holds (Wigfield et al., 2016).</td>
</tr>
<tr>
<td><strong>Attainment Value</strong></td>
<td>Motivational Determinates (Battle, 1965, 1966)</td>
</tr>
<tr>
<td></td>
<td>SEVT built off of Battle’s conceptualization of attainment value, and so the two theories’ constructs are very similar.</td>
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<tr>
<td><strong>Relative Cost</strong></td>
<td>Social Cognitive Theory</td>
</tr>
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<td>Cost in SEVT refers to what is given up doing the task. Effort cost can be a type of cost. Effort is included as a behavioral process in SCT, though other types of cost (time with friends, time on other activities) is not included in SCT.</td>
</tr>
<tr>
<td></td>
<td>Attribution Theory</td>
</tr>
<tr>
<td></td>
<td>Under the casual ascriptions in attribution theory, effort is included. It has similar similarities and differences to cost as outlined in SCT’s use of effort.</td>
</tr>
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Subjective Task Values

Eccles and colleagues took Battle’s (1966) approach of viewing the relationship between expectancies and values as correlated concepts (Wigfield & Eccles, 1992). For the subjective task value (STV) construct in SEVT, Eccles and Wigfield explicitly included and measured specific task values also called achievement values. These subjective task values include 1) attainment value, 2) interest/intrinsic value, 3) utility value, and 4) relative cost. These values work together to strongly predict academic choice (e.g., Durik et al., 2006; Musu-Gillette et al., 2015; Simpkins et al., 2006; Wigfield & Eccles, 2000).

Attainment Value. Battle (1965, 1966) coined the term “attainment value” which consisted of absolute attainment as the overall importance of a task value and relative attainment value as the importance as it related to other tasks (Schunk et al., 2014). Early research by Crandall and colleagues found that attainment was a predictor of academic choice in early elementary students (Crandall et al., 1962). Eccles, Wigfield, and colleagues (1993) built off this idea of attainment value and included it as one of the primary constructs that make up a person’s subject task values. Attainment value in SEVT is defined as the “personal importance attached to doing well on, or participating in, a given task” (Eccles, 2005, p. 109).

The importance placed on a task is closely tied to one’s own identity. If one holds being academically talented in math as a core part of who they are as a person, participating in an organization such as Mathletes would reinforce that self-held notion that they are a smart math person, and would provide high attainment value for them. Conversely, if they did not see themselves as an artistic person, attending a poetry reading might hold low attainment value for them since it does not reinforce an aspect that is core to who they are or how they see themselves. This reinforcement of self-schema or self-held identities is essential in explaining
how a person might view a task as important while another devalues the same task for themselves.

Conceptualizing attainment value this way has not been fully realized in the research though. Since popular measures of attainment value have been limited in their ties to self-schema and identities (Eccles & Wigfield, 2020), the definition used is normally more limited. In fact, Wigfield and Eccles even simplified attainment value to, “the importance of doing well on a given task” in some of their own research (Wigfield & Eccles, 2000, p. 72).

**Interest.** The next component of STVs is interest or enjoyment value. Interest, sometimes called intrinsic value even within various iterations of SEVT, is the “enjoyment one gains from doing the task” (Wigfield & Eccles, 2000, p. 72). A person who engages in a task because they enjoy it is likely to get more deeply involved and spend more time on that task. It is important to make the distinction between intrinsic motivation and intrinsic value. Intrinsic motivation causes or encourages a person to begin a task which is the antecedent to the action. Intrinsic value on the other hand is the enjoyment or value inherent in doing the task itself. Not only are they conceptually different, but they also come from different theoretical perspectives (Wigfield & Eccles, 2020). Oftentimes tasks with high interest also hold high attainment value for the person.

**Utility Value.** Utility value is the third construct that makes up subjective task values. Wigfield and Eccles defined it as “how a task fits into an individual’s future plans” (2000, p. 72). If a person wants to major in mechanical engineering in college, they will likely place a higher value on taking difficult math courses in high school because of their usefulness to that future major. Utility value is habitually linked to extrinsic motivation which normally provides the catalysis of doing a task because it is a means to an end (Eccles & Wigfield, 2020). When a
person holds a future goal as central to their identity and the task itself is also key to the fulfillment of that goal, then the linkage between utility value and attainment value is very high. For example, if a person sees themselves as a future astronaut, not only is this a future goal but an inherent part of their identity and self-schema as well. Tasks such as majoring in aerospace engineering, chemistry, or computer science will have high utility value as well as attainment value.

Work has been done to parse out the various types of utility value that relate to the construct’s impact on choice (Gaspard et al., 2015; 2017). Gaspard et al. (2015) expanded utility to five parts: utility for school, utility for a job, utility for math in daily life, social utility, and general utility for one’s future. However, parsing out utility to separate subdomains does not enhance its overall impact on student choice. Eccles and Wigfield (2020) postulate that even though separating the various types of utility may be a requisite line of research, it is more beneficial to investigate the social and psychological impacts on these various portions of utility value.

Relative Cost. Relative cost is the one subjective task value item that is normally modeled with a negative relationship to academic choice and persistence. While it was originally discussed in relation to STVs in the 1983 iteration of the model, it was included as one of the four primary components in the model the following year (Wigfield & Eccles, 2020). Cost relates to “what is lost or given up or suffered when doing any particular activity” (Wigfield & Eccles, 2020, p. 169). Cost can be related to the following 1) effort cost, which is how much work will I have to put in, 2) relative cost, which is if I do this task, I won't be able to do that other task, and 3) emotional and psychological cost which encompasses failure cost, which is how will I feel if I try and don’t do well on the task. Individuals weigh these costs for all tasks,
though not always in equal ways. If taking those harder math courses in high school would limit the amount of time a student has to spend with friends, then they may see the relative cost as too high to be worthwhile even though they may excel at math and have very little effort cost.

Much work has been done to investigate the nature of cost in achievement tasks and choice, so much so that an argument has been made to change the name of the theory to include cost directly in the title (Barron & Hulleman, 2015; Eccles & Wigfield, 2020). Work by Perez and colleagues (2014) found that effort, opportunity, and psychological cost were all empirically distinct and impact college STEM choices. Although some models show cost directly impacting choice (e.g., Gaspard et al., 2015, 2017; Watt et al., 2019). Eccles and Wigfield (2020) argue that the construct remains under subject task values, but that more work is needed to parse out the various weights assigned to different aspects of cost.

Socialization and Student Background in SEVT

The exogenous variables that make up the left portion of the SEVT model deal mostly with demographic, socially constructed beliefs, and experiences. These together impact students’ expectancies for success and failure as well as their STVs. Students are perpetually cognitively processing the messages of those around them like their parents, teachers, and friends which in turn influence how they feel about a given task.

Socializer Beliefs and Behaviors. Students develop in an environment with other people. Though not all students share similar social networks, many students have a parent or parent figure. The beliefs of these individuals impact how students view themselves and the world around them. For instance, when parents believe that math is important, students are likely influenced by that and thus would have higher math task value (Harackiewicz et al., 2012). Eccles (1993) did extensive work mapping out the factors that make up parents’ socialization and
how that plays an important role in students’ motivational beliefs. Schools also play a prominent role in the socialization of beliefs (Eccles & Wigfield, 2020). Students spend most of their day in school and inside various classrooms. The characteristics of the classroom including teacher-held beliefs can impact students’ engagement, self-concept, and task values (Wigfield et al., 2015).

**Cultural Milieu.** In this construct Eccles and Wigfield represent the “very macro and distal socio-historical-cultural level” of influencers (2020, p. 2). Things like socially constructed gender roles, such as boys are inherently wired to do X, but girls are wired to do Y, influence students’ beliefs. These stereotypes and beliefs begin as early as age three and continue throughout a person’s life (Ruble et al., 2006). Additionally, cultural contexts also work to impact students’ achievement motivation (Eccles & Wigfield, 2020). It is well established that different cultures value things in distinct ways. Family demographics are also captured in this factor. Cultural notions around single parent or split-family households are represented here. These values, such as collective/individualistic ideals or family/career importance, all serve as a lens through which students view their experiences.

**Personal Characteristics.** Student’s background and characteristics also influence their values and beliefs. Birth order, gender, and race are a few relatively stable demographics which influence how a student views their goals, experiences, and social contexts. Gender has been a primary focus for SEVT as it was originally created to answer questions surrounding gender disparities in STEM (Eccles & Wigfield, 2020), however many more student characteristics come into play. Students’ racial background serves as a context that builds into identity which is part of the self-schema.

**“Perceptions of…”** This construct named “Perceptions of…” is the individuals’ perception of the three previously discussed constructs, socializer’s beliefs, person
characteristics, and cultural milieu factors. Those social-cognitive scholars interested in origins of academic self-concepts (ASC) often look to the sources of information one uses to form ASCs, i.e., the three previous factors, and then the “interpretive processes link experience to the formation of ASCs and [expectations for success]” (Eccles & Wigfield, 2020, p. 9). The later potion, the interpretive process, is what is represented by the “Perceptions of…” and “affective reactions and memorizes” boxes. For instance, if a parent believes that intelligences is a stable trait that is immutable i.e., a socializer’s belief, their child could internalize that or could reject that notion outright. This perception of their parent’s belief then impacts their self-schema.

One prominent component of this factor is how students internalize and perceive messages about gender and social roles. The structural systems are in place that perpetuate gender, racial, and social roles within the educational system. Students take in information about how different groups should behave in different contexts, consciously and subconsciously. They then reflect on these systems and messages and make their own judgements about them. Additionally, students weigh various activities and the demands and rewards associated with them.

“SEVT is both situationally specific and culturally bound” (Eccles & Wigfield, 2020, p. 2), meaning that even with the same information two students may interpret a task’s value differently based on their contexts. These four constructs work together to influence and shape a person’s view of themselves and future tasks. Eccles and Wigfield (2020) did note that each box was meant to represent a general category, and each box might not have the same influence on a student at any given time. Instead, they work concomitantly to influence students’ cognitive processes impacting their achievement related choices and outcomes. Although unique factors unto themselves, they are not always easily or practically captured. Instead, most studies use
direct measures of gender, race, SES, and parental involvement to represent the social and culture influences that impact students’ choices and actions (e.g., Attewell & Domina, 2008; Byun et al., 2015; Watt et al., 2006).

**SEVT Outcomes**

Academic achievement and choice are influenced by all the previously discussed constructs. All the exogenous variables work concomitantly to predict a student’s choice and their performance, which will later influence their task values, expectancies, self-schemas, and goals. Academic performance is often measured via standardized test scores, grades, or ability tests and tasks. Choice on the other hand is normally measured in relation to the person’s engagement or persistence with the task or subject (Schunk et al., 2014). Most often, STVs more strongly predict choice meanwhile expectancies predict future performance (Eccles & Wigfield, 2020).

**Past Experiences**

As students move through their educational journey and make these achievement-related choices and performances, those then become their own past experiences. This process creates the cyclical nature of the SEVT model, which is represented by the dashed “Across Time” line at the bottom of Figure 1. Students’ past achievement-related experiences could be prior grades they earned, how many sight words or multiplication facts they got right, or even their enjoyment and ease of reading a book they selected. Students internalize how they performed in the past on similar tasks and how those around them viewed their past successes and failures.

Though this area of the model has received less focus (Eccles & Wigfield, 2020), it is the basis for how students begin to interpret their experiences. When a student is successful in math in elementary school, they may take that success and interpret it as being mathematically
talented. In turn this will work to shape their self-concepts and identities as well as the value they place on math-related tasks in the future.

Students’ achievement motivation consists of a complex social cognitive process by which students develop self-beliefs and come to value tasks which then influence their choices and performance in academics. Eccles, Wigfield, and their teams articulated the social and cultural influences that impact students' beliefs about tasks and what they expect. They parse STVs into four components: interest, attainment value, utility value, and relative cost. Students place weights on these four components based on the situation at hand and thus can ask, ‘why should I do this task?’ (Schunk et al., 2014). On the other side, students also cogitate on their goals, identities, and self-perceived abilities to ask the question, ‘am I able to do this task?’ which makes up their expectancy beliefs. These two questions and their underlying components work together to impact choice and performance in academics.

**Review of Current Research**

**Mathematics Course-Taking in High School**

Although a plethora of research exists focusing on STEM degree attainment and career pursuits, little has been effective in moving the needle for minority students. As mentioned previously, White students earned 56% of STEM degrees while Black students earned 7% and Latinx/Hispanic students earned just under 12% of the bachelor’s STEM degrees awarded in 2018–2019 (NCES, 2020). Students who have taken fewer or less challenging STEM courses in high school often are underprepared for the level of rigor in college STEM fields (Chen, 2016). Legewie and DePrete (2014) found that schools that had stronger STEM curriculum and higher courses showed significant positive effects on STEM major intention in college.
Mathematics course-taking in high school is linked to numerous positive outcomes in the STEM pipeline. In fact, Byun and colleagues argued that “mathematics is a gatekeeper” to students’ future success in education since they found that course-taking was highly predictive of math achievement and college-going behaviors (Byun et al., 2015, p. 439). The more math a student takes in high school the more likely they are to pursue a STEM degree or career (Adleman, 2006).

It is important to note that course-taking can be measured in various ways. In the past, math course enrollment was often measured through the number of credits a student took in math during high school. However, as states have changed graduation requirements, more students are required to take a minimum number of math credits to earn a high school diploma (Gao, 2021). Since most students are forced to take at least three to four math credits, looking at what those credits are, becomes more crucial than just the number taken. Burkman and Lee (2003) conducted a review of the NCES:88 transcript data and found that categorizing math courses into an eight-level pipeline produced the most robust results when looking at student achievement and learning compared to other models such as the sum of math credit earned. They also found that students who took math at the middle and most advanced levels were more likely to indicate they would pursue STEM in college.

Research has shown that advanced course-taking, across all subjects, but specifically in math, improves academic outcomes like achievement, college enrollment, success in college courses, and bachelor’s degree graduation rates. Students who take more advanced coursework show more gains in math achievement at the end of their senior year. Bozick & Ingels (2008) found that students who took advanced math courses gave more correct answers on a math achievement measure, and their increase in correct answers was typically found in the advanced
skills section of the test. Interestingly a large amount of the variance in math achievement and course-taking behavior in this study was explained by background characteristics, specifically SES, and prior academic achievements, like eighth-grade test scores and grades.

Another research team, Attewell and Domina (2008), looked at curriculum intensity which “connotes both greater intellectual difficulty and breadth of study” (p. 53) for students. They found that students taking math harder curriculum had significantly higher test scores and were more likely to enroll in college. Echoing previous research, they also found that students enrolled in the hardest curriculum quintiles were more likely to graduate college than their peers taking less rigorous courses. Similar to Bozick and Ingles, Attewell and Domina found that lower SES students were more likely to take a less intense curriculum throughout high school.

Adelman (1999, 2006) found similar though more stark differences in graduation rates when looking at different course-taking behaviors. Adelman found that “that every step up the math ladder multiplies the odds of earning a bachelor’s degree by roughly 2.5” and that students taking beyond Algebra 2 in high school showed the greatest odds of completing a bachelor's degree. In fact, the odds of earning a bachelor's degree were 7.52 to 1 for those taking calculus in high school (Adelman, 2006, p. 30). Adelman did highlight that a selection bias is normally present when looking at students' highest math course taken. Students who take more advanced courses are often more interested in math and have higher scores, thus priming them for success in college in general (Ainley & Ainley, 2011; Regan & DeWitt, 2015). Leow and colleagues used propensity score matching to account for this selection bias and still found substantial math achievement gains for students who took harder math and science courses in high school (Leow et al., 2004).
Champion and Mesa (2017) investigated the different tracks in high school curriculum that could potentially led students into calculus during high school. Their rationale was that if a student did not take the prerequisites in time (e.g., Algebra I in eighth or ninth grade) then there would be no possibility that the student could take calculus their senior year even if their desire and grades were there. The student would simply not have the prerequires to enroll in that course during high school. They found that certain tracks, along with malleable (i.e., motivational factors) and non-malleable (i.e., ethnicity) factors, work together to influence roughly which of the roughly 20% of students complete high school calculus.

Tyson and colleagues used the math pipeline categorization by Burkeman and Lee and found that students taking advanced math were more likely to earn a STEM degree and that almost half of students earning a STEM bachelor's degree took Calculus I or higher in high school (Tyson et. al., 2007). The researchers also looked at STEM degree completion by math coursework and race and gender. They found that women were less likely to pursue a STEM degree, but that fewer Black and Latinx/Hispanic students were less prepared for college STEM than their white and Asian peers. Wang (2013) found that exposure to more math and science courses was an even better predictor of STEM intent than academic achievement. Knowing that taking more rigorous math courses in high school leads to higher math achievement and STEM degree attainment, begs the question, what impacts math course enrollment in high school?

**How SETV Factors Impact High School Math Course Enrollment**

As discussed in the framework, expectancies and values play a large role in a student’s achievement-related choices and expectations for their future. Students who value STEM and have had positive previous experiences are more likely to pursue STEM majors and careers later in life (Lent et al., 2018; Sahin et al., 2017; Wang, 2013). Both values and expectations work
concomitantly to influence students’ STEM choices, such as what type of math to take in high school and their performance, like math GPA and test scores. There is substantial evidence that value-beliefs are more directly tied to choice, and expectancy-beliefs largely impact performance (Guo et al., 2015; Marsh et al., 2005; Safavian, 2019; Trautwein et al., 2012). When a student values math, for example seeing its utility for their future job or through simply being interested in the topic, they are more likely to engage with and pursue educational opportunities that promote connections in math. Similarly, as students have previous success in and identify as a math person, they are more likely to succeed in math. Though each factor provides a direct path to either choice or performance, both work simultaneously to predict advanced math course-taking in high school.

**Self-Schema, Goals, and Expectancies.** Suárez-Álvarez, Fernández-Alonso, and Muñiz (2014) looked at the impact of self-concept, expectations, motivations, and socio-economic status (SES) on academic performance through structural equation modeling. They found that overall, these factors explained 72% of the variance in academic performance, but that self-concept had the highest predictive power. Ability beliefs which are closely linked to self-efficacy also play a role in students' choices to take advanced math courses in high school. Bozik and Ingles (2008) found that “those who hold higher educational plans tend to take more advanced courses while those who set lower educational goals tend to take fewer advanced courses” (p. 20). In fact, 32% of students in the highest quintile of math self-efficacy took calculus, while only 9% of those in the lowest self-efficacy group enrolled in the same course (Champion & Mesa, 2018). Simpkins and Davis-Kean’s (2005) work which looked at group clusters based on self-concept and values examined if those clusters could predict the number of total math courses and the number of advanced math courses taken in high school. They found that when students
were in the high self-concept/high value or high self-concept group students took more total and advanced math credits.

**Subjective Task Values.** On the other hand, subjective task values in the SEVT model have a plethora of research to support their importance in the STEM pipeline. Numerous studies spanning over 30 years have documented their importance and influence on students’ choices to take STEM courses, leave or persist in colleges, and eventually pursue a STEM degree (Benbow & Minor, 1986; Perez et al., 2014; Simpkins et al., 2006; Watt et al., 2006). As students value math and/or STEM, it is hypothesized that they will take more advanced math credits in high school.

To test this, Safavian (2019) conducted multi-group structural equation modeling for Hispanic youth. They found that for ninth graders, “judgments about their ability and confidence in math” were highly predictive of math performance for both genders after controlling for prior achievement and SES (Safavian, 2019, p. 4). Though less pronounced, expectancies were also predictive of the number of advanced math courses taken. All four components of subjective task values in the SEVT model were examined. Interest value was most strongly associated with advanced course-taking, as measured by the total number of advanced math credits earned, after a marker for university eligibility. For boys, utility value was a strong predictor of advanced math course-taking, but not for girls. Attainment value and cost value were highly predictive of total advanced credits earned for girls. In fact, for every SD increase in cost, girls' likelihood of taking advanced math courses decreased by 37%. Conversely, boys did not appear to factor in cost value when making credit-related choices. Though their evidence is strong that values and expectancies predict advanced math course-taking for Latinx/Hispanic youth, research on other racial groups is needed.
Intrinsic and utility values both predicted STEM affinity (Ball et al., 2017) which helps students from leaking out of the STEM pipeline. Other subjective task values have proven to be integral to students' STEM-related choices. Interest in STEM and math, in particular, has been a driving force in students’ STEM choices (Ainley & Ainley, 2011; Regan & DeWitt, 2015). Maltese and Tai (2011) found that interest was a better predictor of STEM choices than achievement. Their findings have sparked numerous studies and interventions to promote STEM through students’ motivational values (e.g., Nugent et al., 2015; Wang et al., 2015). An earlier study by Watt and colleagues (2006) looked at the U.S. and Australian high schoolers and the impact of expectancies and values on achievement and participation in math for boys and girls. Since a number of the math variables, i.e., ability beliefs, interest, expectancies, etc., showed high interclass-correlations they modeled them separately and by country. They found that for both boys’ and girls’ math intrinsic value in their sophomore year significantly predicted math participation, the number of math courses taken, their senior year even when controlling for eighth-grade math achievement. Importance or attainment value was a significant predictor of the number of math courses for girls, but not for boys. The research shows that subjective-task values contribute directly to students' course enrollment choices in high school.

Clearly, task values and self-schemas like goals or expectations for future success and valuing of math are prominent factors in students’ choice to take advanced math courses in high school. Together they work to predict future STEM engagement and success. However, motivational factors alone do not explain all the variance in math course enrollments. Instead, it is prudent to also consider students’ backgrounds and how those may also play a role in encouraging or dissuading students from enrolling in advanced math during high school.
Student Factors Impacting High School Math Course Enrollment

Prior Achievement. As Eccles and Wigfield theorized in the SEVT model, prior academic achievement has a strong impact on achievement-related choices and performance for students. In Burkman and Lee’s analysis, they found that while race, SES, and gender did impact high school math course enrollment, eighth-grade math achievement was the dominant predictor of taking more advanced math courses (2003). Attewell and Domina (2008) modeled how eighth-grade math test scores and grades impacted their high school curricula. They found that for every one standard deviation increase in eighth-grade course grades, their high school curriculum intensified by 0.22 standard divisions (SD). Additionally, for each standard deviation increase in eighth-grade math scores, there was an associated 0.29 SD increase in math course intensity in high school. Coupled together it makes sense that previous math achievement impacts advanced course-taking in high school.

Background Characteristics and Cultural Influences

Socioeconomic Status. Extant literature shows the impact a student's socio-economic status (SES) has on their academic journey. Numerous negative outcomes are associated with low SES and begin as early as kindergarten (National Research Council, 2009). These outcomes can range from achievement-related such as test scores (Hussar, 2020) and degree completion (Kena, 2015) to outcomes associated with attitudes and behaviors like educational aspirations (Guo et al., 2015), college-going behaviors (Kena, 2015), and mathematical self-efficacy (Wu, 2016). Consonant among the finds is that students who come from more affluent backgrounds often outperform their economically disadvantaged peers even accounting for all other factors.

One area that SES plays a large role in a student’s educational career is in their choice of courses in high school. Students from low-SES backgrounds often take fewer and less rigorous
STEM courses in high school. Tyson and their team found that students from higher SES backgrounds take more high-level math and science courses (Tyson, et al., 2007). Burkman and Lee (2003) found similar results. At both levels of academic math credit, the total number and advanced courses, SES played a significant role in predicting the number of higher math classes a student would take. Interestingly though, at the highest level, advanced math, SES was not a significant predictor in the number of credits but remained significant when looking at a binary outcome of taking advanced math. They found that low SES students who do end up taking advanced math courses produce significantly more gains than high SES students taking the same courses (Byun et al., 2015). Conversely, Long’s analysis of state-level data from Florida showed that low SES students showed the least amount of gains in college readiness when looking at advanced course-taking, and the lowest gains were found in mid-range math courses (Long et al., 2009). This type of differential outcome indicates interactions between other factors may be different depending on a student's economic background.

**Gender.** Gender disparities in choice and achievement in STEM pursuits have been a common area of interest in educational research. Women are less likely to hold a STEM degree than men, even though they hold 57% of bachelor’s degrees in all fields (NSB, 2019; Wang & Degol, 2017). Some have argued that the gender gap in high school math participation has all but disappeared. Tyson and colleagues found that although women were less likely to pursue a STEM degree in college it was not due to lack of preparation in high school as measured by advanced course-taking (Tyson et al., 2007). Even when academic achievement differences are present it is not the primary cause of gender disproportions in STEM (Diekman et al., 2019; Hyde et al., 2008; Lindberg et al., 2010). In fact, women enroll in Algebra 2 and precalculus at greater rates than men though no differences are found for calculus and other types of advanced
math (IES, 2011). Alternatively, You and Sharkey’s analysis of the 2002 Educational Longitudinal Study found that girls took more advanced math courses than boys and that racial background and SES both impacted the number of credits taken (2012). Although the gender gap for advanced math course-taking appears to be shrinking, if not altogether removed, controlling for gender differences in models remains prudent.

Simpkins and Davis-Kean’s (2005) work looked at group clusters based on self-concept and values examined if those clusters could predict the number of total math courses and the number of advanced math courses taken in high school. Though gender differences were present for the total number taken, no gender differences were found for the number of advanced math credits for the two cluster groups. For Black males, math identity was strongly tied to math test scores (Jackson et al., 2020). Self-concept has been shown to have a stronger impact on math achievement than utility value. Utility on the other hand was a dominant predictor of future STEM aspirations (Guo et al, 2015). Research has clearly shown that while self-concept, expectancies, and identity do impact choice, they more often have a more direct influence on performance.

**Race.** A student's racial background can play an important role in their education. Not only is race a part of one’s own identity, but many educational outcomes also vary by race even when controlling for other factors. Underrepresented minority students often take fewer and easier math and science courses (IES, 2011; Kelley, 2009) and are often enrolled in remedial and below-academic level math courses at a higher rate (Kao, & Thompson, 2003). White and Asian students on the other hand frequently complete higher-level math courses in high school. For example, 45% of Asian students and 18% of White students completed calculus, but
Latinx/Hispanic students and Black students had a 10% or less completion rate (de Bray et al., 2019).

These demographic statistics of advanced course-taking often hold true even when accounting for the complex and interwoven factors that impact students’ course enrollment choices. When looking at advanced courses, Dalton and colleagues found that 14% of African American and 15% Latinx/Hispanic students enrolled in precalculus in high school compared to their White peers whose enrollment rate was 21% even after controlling for other factors (Dalton et al., 2007; Ingles & Dalton, 2008). Tyson and colleagues found that Black and Hispanic/Latinx students took fewer high-level math and science courses than their White and Asian peers and that the “primary point” in their departure from the STEM pipeline happens in high school (Tyson et al., 2007, p. 265). However, while Attewell and Domin originally found racial differences in curriculum intensity, i.e., harder courses, but when SES was controlled for in their model all differences were either negated or reversed (2008).

Although race plays a role in various academic outcomes, applying a one-size-fits-all approach is inappropriate. Research shows that there may be variation not only within the outcomes but also in the effects and interactions of the factors. Long et al. (2009) found that African American and Asian students saw smaller benefits in college readiness in math when taking advanced math courses compared to their White peers. However, Latinx/Hispanic students saw differing benefits compared to White students; when they enrolled in Algebra 2, the benefits decreased, but if taking precalculus or higher, they saw greater benefits.

Similarly, Byun et. al.’s (2015) study sought to investigate the impact advanced course-taking had on math achievement and college enrollment. They found that the impacts on math achievement were greater for low SES and White students compared to affluent or Black
students, but no racial differences were found for college enrollment. Anderson and Ward (2013) also found that when modeling STEM high school motivational impacts on STEM persistence, the impacts of those factors differed by race. In fact, they found that for high-ability Latinx/Hispanic students, higher utility value was a predictor of STEM persistence, but not for White or Black students. In the model for Black students, math achievement was a predictor but was removed from the models for White and Latinx/Hispanic students. Additionally, interest and math attainment were not significant for White students but were for Black and Latinx/Hispanic students. These findings highlight the nuanced and often differing ways race impacts students' educational behaviors, expectations, and achievements.

Additionally, stereotypes based on gender and race play a role in students’ beliefs about and behaviors surrounding math course-taking. By early elementary age, children uphold an ingrained stereotype that math is for boys, not girls and that math is for people of Asian descent (Cvencek et al, 2011; Cvencek et al., 2014). Often members of the groups associated with the negative stereotype have worse outcomes simply because they are aware of the stereotype, and it hasn’t been challenged. This phenomenon is called “stereotype threat” and is a documented cause for women’s, Blacks’, and Latinx’s underperformance on academic-related activities (Aronson & Steele, 2005, Good et al., 2008). When students perceive and believe academic racial stereotypes, i.e., Black students do cannot achieve at the same level as their White peers, students have lower self-concept of their academic abilities (Okeke et al., 2009). The converse is also true; when negative stereotypes are associated with one racial group it serves to promote ability-performance of members outside that group (Walton & Cohen, 2002). One specific and well documented gender-stereotype that negatively impacts girls is their parents’ gender-based math-ability beliefs (Eccles & Jacobs, 1986; Gunderson et al., 2011).
**Parental Influences.** Parents exact a large influence on their children’s academic and achievement-related choices. Research has shown that parental expectations impact students’ own future expectations for themselves and that both can equally influence achievement choices (Bandura et al., 2001; Froiland et al., 2013). Additionally, parents’ educational aspirations for their children early on can improve student’s motivational outcomes into high school (Fan & Williams, 2010). Froiland and Davidson (2016) found that parents’ expectations predicted math course-taking and likelihood of advanced math course-taking even after controlling for demographic influences. As parents’ expectations for their children are elevated, the students appear to take harder academic tracks and perform better overall (Marcenaro-Gutierrez & Lopez-Agudo, 2017).

Though parents can sometimes sway which courses their students take, rules and policies within various school systems can limit their direct influence over their student’s course schedule (Useem, 2010). Interestingly the child’s and parent’s gender can impact their level of influence on math course-taking. You and Sharkey (2012) found that a father’s expectations significantly impacted their daughter’s math course-taking choices, while sons were influenced by their mother’s expectation. The reciprocal influence for both groups was nonsignificant. Similarly, parental expectations and influences can vary by culture and racial groups (e.g., Glick & White, 2004; Suizzo & Stapleton, 2007; Yamamoto & Holloway, 2010).

Not only can parental expectations impact student choice and achievement, but parents’ involvement in their child’s schooling can exert influence as well. A meta-analysis by Jeynes (2012) found that parent involvement was a significant positive predictor of student achievement across numerous studies. Overall, parents continually sway their children’s achievement-related choices throughout their elementary and secondary educational careers.
School Factors Impacting High School Math Course Enrollment

Students do not receive their education in a silo. The culture, climate, and demographics of the school itself can impact a student’s academic achievement and educational goals. Indeed, Rumberger and Palardy (2005) found that “where students attend school has a major impact on how much they learn” (p. 2018). Tyson and colleagues' analysis indicated that important differences in high-level STEM course-taking may be at the school level instead of solely at the student level (Tyson et al., 2007).

Schools that have a high rate of poverty among their student body often negatively impact their students' academic outcomes. Caldas and Bankston (1997) found that even when controlling for an individual’s SES level, race, sex, study hours, and English proficiency, students who came from more affluent schools had higher academic achievement compared to students attending schools with a higher poverty rate. More recently, Kastberg and colleagues found that students’ mathematical literacy is significantly different depending on the percentage of students in the school who received free and reduced lunch. Schools with free and reduced lunch ratios had lower scores, and as the percentage of students on free and reduced lunches decreased, test scores significantly improved (Kastberg et al., 2016).

One explanation for the negative impacts of school SES on student achievement and course-taking is the resources available to the study body. Schools with a high poverty rate often do not have the same course offerings as high-SES schools (Oakes & Saunders, 2004). Alderman (2006) found that “students from the lowest SES quintile attended high schools that were much less likely to offer any math above Algebra 2 than students in the upper SES quintiles” (p. xvii). Additionally, Xie and colleagues’ (2015) review of the literature found that school funding and resource availability impacted the way students engage with and excel at STEM fields.
School type, such as private or public, has also been shown to influence students’ math attainment in high school. Xu and Kelly (2020) found that Catholic schools often offer more advanced math courses relative to the mid-level courses. Some of that variance though was explained by the selection process based on family background characteristics since parents within the higher educational attainment brackets, dual-parent households, and more affluent families enroll their students in private schools at higher rates (Wang et al., 2019). The advanced course-enrollment advantage between the private and public sectors is shrinking yet remains an area of disparity that researcher must acknowledge (e.g., Bryk et al., 1993; Carbonaro & Covay 2010).

School location can also impact a students’ academic achievement and performance. Schools from urban areas often serve more minority and poorer students and have lower graduation rates, though they have higher college-going rates (NCES, 2011, 2013a, 2013b 2015). Hopkins (2005) found that suburban/township schools had the highest math ACT scores as well as standardized end-of-year achievement tests, followed closely by rural schools. Interestingly though, poorer students in rural areas faired far better on math achievement tests than equally impoverished students in urban or suburban areas. Work by Cogan and colleagues found inconsistent results of school location on student math tracks and contended that there was inadequate support to show meaningful differences by location on students’ course-taking (Cogan et al., 2001). Though mixed results were found for school-level influences, it is important to consider the context in which students learn and make their educational choices.

Research Interests

Extant literature has shown that student background characteristics, motivational beliefs (i.e., expectancies and values), and school-level factors shape students’ math achievement-
related choices. When students hold STEM-related goals, have high math ability beliefs, or hold a math identity they are more likely to show higher math achievement and select more rigorous courses in high school. Additionally, students who place a high value on math through interest, its usefulness or utility, or its important or attainment value enroll in harder math courses at higher rates. Stable background characteristics like a students’ gender and race can influence students’ choices, though their socioeconomic status has proven to consistently be the most important factor in achievement related choices for high schoolers. School context can also impact students’ course-taking decisions. Coupled together, there are many factors inflecting students’ choices and Situated Expectancy Value Theory can help guide the investigation into how students come to make the choices that can later shape their college and career aspirations.

Though there is extensive literature focusing on math course-taking in high school and how students’ values and expectancies influence on their academic-tracks, there are still gaps in the literature. One specific focus that is often cited as an area of future research is in the differential impacts based on racial/ethnic groups (Anderson & Ward, 2013; Safavian, 2019). Many studies focusing on STEM math achievement and choice include race as a simple factor or control, yet few examine the impacts within an individual racial or ethnic group (e.g., Maltese & Tai, 2011; Byun et al., 2015). Eccles and Wigfield (2020) called for more work on how culture, ethnicity, gender, and the interactions of them influence students’ expectancies and values.

Some studies have begun to look at these factors by modeling each individual group separately, so as to home in on the driving factors for each group (e.g., Anderson & Ward, 2013; Howard et al., 2019). However, both studies have methodological shortcomings. Anderson & Ward’s (2013) study using the HSLS:09 data set incorrectly categorized certain SEVT factors and left many out, while Howard’s and Anderson (2019) used single-level regression thus not
accounting for school-level variance. Though there has been an uptick in the use of multilevel modeling in recent years, many of the studies looking at these factors continue to use single-level regression models, or when using more rigorous methods, use single-level structural equation modeling (e.g., Froiland & Davidson, 2016; Safavian, 2019; Suárez-Álvarez et al., 2014), yet these do not account for the school context in which student’s choices and performance occur.

Building off the extant literature surrounding advanced math course-taking and acknowledging the gaps that currently exist in the literature, this study sought to examine the motivational, contextual, and background influences on advanced math course-taking in high school, and to see if those impacts differ by students' racial or ethnic background. The relationship was examined by investigating each of the following research questions:

1. How do background characteristics and prior academic experiences impact advanced math course-taking in high school? How do the impacts differ for Black, Latinx/Hispanic, and White students?

2. In what ways do student’s views of the value of mathematics and expectations for success in math during freshman year of high school influence high school advanced math course-taking for different racial groups after controlling for background characteristics and prior academic experiences?

3. What school-level factors influence advanced math course-taking in high school?
Chapter 3: Methods

This chapter first describes the study design and the HSLS:09 dataset sampling procedures. Next, follows an overview of the measures utilized in the study and then a synopsis of the data analysis including preliminary analysis and procedures utilized.

Research Design

This non-experimental, longitudinal study utilized multilevel modeling to examine how school context, motivational and background student characteristics impacted advanced math courses-taking in high school and was guided by Eccels and Wigfield's (1983, 2020) Situated Expectancy Value Theory. This study used factors measured during students’ ninth-grade year in high school to determine what, if any, impact they had on the highest-level math course a student took as measured by their final high school transcript. Students were nested in schools creating a two-level model. Each racial/ethnic group had a separate model and findings are reported separately for each group.

Sample

The sample came from the High School Longitudinal Study of 2009 (HSLS:09) and subsequent follow-up studies conducted by the National Center for Educational Statistics (NCES) with support from the National Science Foundation (Ingels et al., 2011). The nationally representative sample consisted of 23,000+ ninth-grade students from 944 schools during the baseline year. Follow-up studies were conducted in 2012 during their junior year, in 2016–2017 where the majority were attending college, along with an update and transcript data in 2013 (high school transcripts) and 2017–2018 (post-secondary transcripts). Students who skipped an item in an earlier iteration were asked the same question on a subsequent survey, so the demographic information was more comprehensive in the follow-up studies.
The HSLS studies sought to “explore secondary to postsecondary transition plans and the evolution of those plans; the paths into and out of science, technology, engineering, and mathematics; and the educational and social experiences that affect these shifts. (Ingels et al., 2011, p. iii). The conceptual model for the study is depicted in Figure 2 and was heavily influenced by the SEVT theoretical framework pictured in Figure 1. Students, teachers, counselors, and administrators completed surveys that all make up the HSLS:09 data.

**Figure 2**

*HSLS:09 Base-Year Student Survey Conceptual Map (Ingles et al., 2011, p. 11)*

For this study three different models were constructed to answer the three research questions. Mirroring the study by Anderson and Ward (2015), each racial/ethnic group, Black, Latinx/Hispanic, and White, was modeled separately.

The full HSLS:09 data set was comprised of 52.1% White students \( n = 13135 \), 10.5% Black students \( n = 2646 \), and 16.2% Hispanic/Latinx students \( n = 4065 \). Data cleaning procedures were conducted removing any student with missing or incomplete data. This left produced a sample with 14.6% Hispanic/Latinx students \( n = 1641 \), 59.0% White students \( n = 6628 \), and 8.4% Black students \( n = 942 \). From there a random sample was drawn from each
racial/ethnic group to equal the smallest group, Black students, so that each racial/ethnic group was comprised of 942 students \( (n = 942, N = 2,826) \).

Students were roughly split by sex (51.9% female) and the majority did not expect to be in a STEM occupation at age 30 (66.9%). The White student group had more students scoring A’s in their eighth-grade math course (44.7%) compared to the Black student and Hispanic/Latinx student groups (28.5% and 30.5%, respectively). Hispanic/Latinx students had the lowest SES rate \( (M = -0.20) \), followed by Black students \( (M = 0.15) \); White students had the highest SES average \( (M = 0.29) \). The students in the sample came from 778 schools and 81.7% of the schools were public schools. Full student and school demographics are reported in Tables 2 and 3.
Table 2

Background Characteristics of Student and School Sample

<table>
<thead>
<tr>
<th>Baseline characteristics</th>
<th>Black</th>
<th>Hispanic/Latinx</th>
<th>White</th>
<th>Combined Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( n )</td>
<td>( % )</td>
<td>( n )</td>
<td>( % )</td>
</tr>
<tr>
<td><strong>Student characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>489</td>
<td>51.9</td>
<td>505</td>
<td>53.6</td>
</tr>
<tr>
<td>Male</td>
<td>453</td>
<td>48.1</td>
<td>437</td>
<td>46.4</td>
</tr>
<tr>
<td>Expected occupation - age 30</td>
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<td></td>
<td></td>
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<tr>
<td>STEM field</td>
<td>325</td>
<td>34.5</td>
<td>275</td>
<td>29.2</td>
</tr>
<tr>
<td>Non-STEM field</td>
<td>617</td>
<td>65.5</td>
<td>667</td>
<td>70.8</td>
</tr>
<tr>
<td>Eighth-grade math grade</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>268</td>
<td>28.5</td>
<td>287</td>
<td>30.5</td>
</tr>
<tr>
<td>B</td>
<td>386</td>
<td>41.0</td>
<td>404</td>
<td>42.9</td>
</tr>
<tr>
<td>C</td>
<td>208</td>
<td>22.1</td>
<td>179</td>
<td>19.0</td>
</tr>
<tr>
<td>D</td>
<td>55</td>
<td>5.8</td>
<td>47</td>
<td>5.0</td>
</tr>
<tr>
<td>Lower than a D</td>
<td>25</td>
<td>2.7</td>
<td>25</td>
<td>2.7</td>
</tr>
<tr>
<td><strong>School characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Unique Schools</td>
<td>441</td>
<td>56.7</td>
<td>446</td>
<td>57.3</td>
</tr>
<tr>
<td>Locale</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>City</td>
<td>139</td>
<td>31.5</td>
<td>139</td>
<td>31.2</td>
</tr>
<tr>
<td>Suburb</td>
<td>168</td>
<td>38.1</td>
<td>165</td>
<td>37.0</td>
</tr>
<tr>
<td>Town</td>
<td>44</td>
<td>10.0</td>
<td>46</td>
<td>10.3</td>
</tr>
<tr>
<td>Rural</td>
<td>90</td>
<td>20.4</td>
<td>96</td>
<td>21.5</td>
</tr>
<tr>
<td>Control</td>
<td></td>
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<tr>
<td>Private</td>
<td>92</td>
<td>20.9</td>
<td>83</td>
<td>18.6</td>
</tr>
<tr>
<td>Public</td>
<td>349</td>
<td>79.1</td>
<td>363</td>
<td>81.4</td>
</tr>
</tbody>
</table>

Notes:

* Calculated with unique schools in the sample.
Measures

Student Demographic Variables

Demographic variables for race (X2RACE) and sex (X2SEX) were from the first follow-up study, since missing values from the baseline survey were captured in the second survey, and thus the variables had fewer missing values. Students who completed the base-year study and not the first follow-up questionnaire had their data copied forward. Students who selected Hispanic/Latinx on the ethnicity item were then asked their race. Most Hispanic/Latinx students selected a race (n = 3,603) although some did not (n = 225). Both groups of these students were categorized as Hispanic/Latinx for this study. X2SEX was recorded so that females were the reference variable (0), and males were coded as 1.

Two composite variables for SES exist in the HSLS:09 dataset, one that closely aligns with previous NCES studies and a second that accounts for school urbanicity. Both variables were functions of parent education, parent occupation, and family income. The first index (X1SES/X2SES/X4X2SES) most closely aligned with previous NCES studies that included a measure for socioeconomic status and was recommended as the variable when seeking to compare results to studies using other NCES secondary longitudinal studies (Ingles et al., 2013). X4X2SES was used as it represents the most comprehensive SES variable in the dataset. Because this composite variable consisted of information about parent education and occupation, this study did not include these variables as separate measures of family demographics in order to avoid collinearity issues. This variable was grand-mean centered when entered into the model.

Prior Academic Achievement

Eighth-grade math performance was included as a predictor variable. Letter grade in mathematics in eighth grade was recorded as an ordinal measure (A, B, C, D, or lower than D)
(S1M8GRADE). Some students indicated that their class was not graded, had a legitimate skip, or had no data recorded; these students were removed the full dataset since no past performance was measured. The majority of students made an A or a B in their eighth-grade math course (34.5% and 40.1%, respectively).

A student's letter grade in eighth-grade math was dummy coded and entered into the analysis with a grade of “lower than D” as the reference variable (0). Treating the eighth-grade math grade variable as ordinal was prudent since there is a logical order to the grades, but the data do not provide enough information to determine the level of difference (i.e., a student with an 89 might earns B, but students with a 90 or 99 would both receive an A for their course.) (Filed, 2018).

**Table 3**

**Means and Standard Deviations of Continuous Measures**

<table>
<thead>
<tr>
<th>Continuous factors</th>
<th>Black</th>
<th>Hispanic/Latinx</th>
<th>White</th>
<th>Combined Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>SD</td>
<td>VIF†</td>
<td>M</td>
</tr>
<tr>
<td>School Poverty*</td>
<td>34.90</td>
<td>26.52</td>
<td>—</td>
<td>38.54</td>
</tr>
<tr>
<td>SES</td>
<td>0.15</td>
<td>0.76</td>
<td>1.17</td>
<td>—</td>
</tr>
<tr>
<td>Math ability</td>
<td>37.03</td>
<td>10.89</td>
<td>1.33</td>
<td>39.35</td>
</tr>
<tr>
<td>Math utility</td>
<td>0.29</td>
<td>0.95</td>
<td>1.24</td>
<td>0.06</td>
</tr>
<tr>
<td>Math self-efficacy</td>
<td>0.20</td>
<td>0.96</td>
<td>1.89</td>
<td>0.05</td>
</tr>
<tr>
<td>Math identity</td>
<td>0.88</td>
<td>1.00</td>
<td>2.13</td>
<td>0.03</td>
</tr>
<tr>
<td>Math interest</td>
<td>0.21</td>
<td>0.99</td>
<td>1.97</td>
<td>0.09</td>
</tr>
<tr>
<td>STEM cost</td>
<td>0.23</td>
<td>.96</td>
<td>1.10</td>
<td>0.07</td>
</tr>
</tbody>
</table>

Notes:

† Variance Inflation Factor: A single-level regression was run that included all predictor variables including nominal and dummy variables to determine if issues of multicollinearity were present.

* Calculated with unique schools in the sample.

**Ninth-Grade Math Ability**

All students took a 40-item math computer-delivered algebraic reasoning test during ninth grade, the base-year study. The test covered six content domains 1) the language of algebra, 2) proportional relationships and change, 3) linear equations, inequalities, and functions,
4) nonlinear equations, inequalities, and functions, 5) systems of equations, and 6) sequences and recursive relationships, and four process domains 1) demonstrating algebraic skills, 2) using representations of algebraic ideas, 3) performing algebraic reasoning, and 4) solving algebraic problems. Algebraic reasoning tests often serve as a proxy for math ability and intelligence measures (Fong & Kremer, 2020; Tirre & Pena, 1993).

HSLS:09 computed the estimated number-right score as a criterion-referenced measure of achievement that represents “the number of items that students would have answered correctly had they responded to all 72 items in the item pool” (p. 28). Of the 40 items, the first 15 items were used to place the students into 1 of 3 performance tracks, low, moderate, or high level. Scores were computed using the IRT three-parameter logistic (3PL) model (Ingles et al., 2011). The final score was the standardized score and a norm-referenced measure of achievement that represented the students' ability in algebraic reasoning compared to all ninth graders in 2009. For this study, the estimated number-right score (X1TXMSCR) was used as a measure of ninth-grade math ability. The maximum score is 72 with a minimum of 0. The actual scores on the measure ranged from 15.9–69.9 with a weighted mean of 38.30 (11.28 SD). When entering math ability into the model it was grand-mean centered.

Mathematics Attitude Scales

Since the HSLS:09 dataset was created with an Expectancy Value Theory framework, several items were included to capture some of the factors included Eccles and Wigfield’s SEVT (2020) model. These items were then used to create scale scores through principal components analysis. Four scales were created for both math and science. The four scales for math utility, interest, self-efficacy, and identity were used in the analysis. All items were standardized using the full HSLS sample to a mean of zero and a standard deviation where higher scores indicated
more positive attitudes toward math. All scales were grand-mean centered when added into the models.

**Math Utility Value.** A measure of math utility was created in the dataset that measured a student's perception of the usefulness of math to their everyday life (S1MUSELIFE), college (S1MUSECLG), and their future job (S1MUSEJOB). These items specifically asked about the uselessness in the context of their ninth-grade math course, so students who were not taking a math course then were removed. Using principal components analysis, a standardized score was created (X1MTHUTI) with a mean of zero. The internal consistency estimate reported by the HSLS authors was acceptable (α = .78).

**Math Interest.** A students' intrinsic value in math, often called interest, referred to the enjoyment they gain from doing math. The scale score for math interest consisted of six items related to the student's current math course. Students reported on their most and least favorite subjects (S1FAVSUBJ & S1LEASTSUBJ) along with if they took the course because they “really enjoy their [ninth-grade math course]” (S1MENJOYS). Three more items had students rate their agreement that “you are enjoying this class very much” (S1MENJOYING), “you think this class is boring” (S1MBORING), and “you think this class is a waste of your time” (S1MWASTE). After reverse coding, the HSLS research team created the composite score, X1MTHINT, using a combination of the items. The internal consistency for this scale reported by the HSLS authors was .75.

**Math Identity.** Math identity referred to the extent to which a student believed they were a “math person”. Two items were used to create this scale. Students rated their level of agreement using a four-point scale from “strongly agree” to “strongly disagree” to the statement “you see yourself as a math person” (S1MPERSON1) and “others see you as a math person”
(S1MPERSON2). Those two items were used to create **X1MTHID** which had an internal consistency of .84, as reported by the HSLS authors.

**Math Self-efficacy.** The last HSLS:09 scale that was created for math was math self-efficacy. A students’ self-efficacy in math represents a student’s self-judgments about their ability to be successful in the ninth-grade math course. Four items comprised the self-efficacy scale. Students rated their confidence on a 1–4 Likert scale on their beliefs, “that you can do an excellent job on tests in this course” (S1MTESTS), “that you can understand the most difficult material presented in the textbook used in this course” (S1MTEXTBOOK), “that you can master the skills being taught in this course” (S1MSKILLS), and “that you can do an excellent job on assignments in this course” (S1MASSEXCL). The resulting **X1MTHEFF** scale variable had acceptable internal consistency (α = .90), as reported by the HSLS authors.

**STEM Expectancies**

Students were asked in the baseline study “as things stand now, what is the job or occupation that you expect or plan to have at age 30?” The NCES research team used the Occupational Information Network (O*NET) code to categorize the occupations. Based on O*NET’s taxonomy six sub-domains were grouped into STEM-related occupations (**X1STU30OCC_STEM1**), e.g., health occupations or life and physical science, engineering, mathematics, and information technology. Almost 60% of the sample selected non-STEM occupations and were coded as 0. Treating the categories as unique sub-domains is imprudent since some of the categorizations are “split across 2 sub-domains” or “unspecified sub-domain.” Instead, the six sub-domains were recoded to create a binary variable with 0 as a non-STEM occupation and 1 as a STEM occupation.
STEM Cost

Four items asked about how the time and effort in both math and science courses together impacted various activities or portions of their lives. The items asked students to rate their level of agreement that, “if you spend a lot of time and effort in your math and science class” 1) “you won't have enough time for hanging out with your friends” (SITEFRNDS), 2) “you won’t have enough time for extracurricular activities (SITEACTIV), 3) “you won't be popular” (SITEPOPULAR), and 4) “people will make fun of you” (SITEMAKEFUN). Since it convolutes math and science, this scale was categorized as STEM cost instead of math cost or science cost.

The researcher emulated the process used by the HSLS:09 team to create a scale-score by using principal components analysis on the four items where all items were forced to load onto a single factor. This process was completed before any participants were removed from the full HSLS:09 sample. This was done since PCA procedures standardized scores to a mean of 0 and standard deviation of 1. Conducting PCA prior to cleaning the data allowed this scale to have the same reference as the HSLS:09 created scales. The scale reliability was extremely high for the four items (α= .99). The items were recoded so that a higher score equated to a higher cost value so that when included in the analysis cost would hypothetically produce a negative relationship with advanced course-taking, which mimics the relationship between cost and choices in SEVT. When cost was included in the model it was grand-mean centered.

School Level Variables

Students were nested within schools since students at the same school tend to share unobserved characteristics that are influenced by their environment (Moerbeek, 2004). When school level nesting is used a larger portion of the variance in the outcome can be explained by
the model. This study had students nested in their ninth-grade school, and school-level variables were included in the analysis based on findings from the literature.

**School Poverty Levels.** The free and reduced lunch program in the United States provides “a proxy measure for the concentration of low-income students” (NCES, 2021). The HSLS:09 data set captured the percent of students who are eligible to receive free and reduced lunch (A1FREELUNCH). This variable had a possible max of 100 and a minimum of 0. It was grand-mean centered when added into the level-2 model. For the schools in this study, the average percent of the student body who was eligible for free or reduced lunch was 34.63 ($SD = 25.49$). White students in the sample attended more affluent schools by an average of four percentage points fewer students qualifying compared to schools in the Black student sample. Schools in the Hispanic/Latinx sample had the highest poverty rates of the three groups ($M = 38.54$, $SD = 28.17$).

**School Urbanicity.** School demographics and performance can vary widely by the school’s location. The HSLS:09 dataset provided an ordinal variable (X1LOCALE) which categorized schools into 1) city, 2) suburb, 3) town, or 4) rural (29.0%, 35.5%, 12.0%, & 23.5%, respectively) (Ingles et al., 2011). Suburban schools were used as the reference variable since it was the largest group (0).

**School Type.** School type, private, public, or parochial, has been shown to impact students’ math course-taking decisions (Xu & Kelly, 2020). The HSLS:09 dataset used (A1SCHCONTROL) to categorize schools into either the public (81.7% of schools) or private (18.3%) sector. Public schools were entered as the reference variable (0) since it was the larger group. Full school characteristics by racial/ethnic group are reported in Tables 2 and 3.
**Advanced Math Course-Taking**

Advanced math course-taking was the dependent variable in the study. In 2013 the HSLS:09 data team attempted to collect high school transcripts on all students in the base-year or first follow-up study. A total of 21,928 transcripts were collected representing 93.6% of the base-year participants. Using the School Codes for the Exchange of Data (SCED), a basic coding procedure was completed for all transcripts. It is important to note that the SCED was not used in previous NCES transcript studies, but was chosen because it provided more detail, had more modern course classifications, and was widely adopted in the K–12 sector (Ingles, 2015, p. 65).

Xu and Kelly (2020) created a robust categorization of math courses by course difficulty in their study. The HSLS:09 dataset contains 66 of the 87 courses outlined in the SCED. Their coding system categorized courses as follows:

1. Less than algebra I,
2. Algebra I or similar level of difficulty,
3. Geometry or equal,
4. Harder than algebra I, but less difficult than algebra II and “courses coded with 4 are courses that transit from 1–3 to 5 or higher,”
5. Algebra II,
6. “Applied math elective courses that include any course that may apply theories or knowledge from algebra II and/or geometry courses,”
7. Algebra III or other high-level algebra-based courses,
8. Trigonometry and mathematic analysis courses,
9. Calculus and other equivalent courses based on pre-calculus, trigonometry, or algebra III,
10. Courses that are harder than calculus (Xu & Kelly, 2020, p. 136).
Some of the SCED course codes were too broad to fit into a single category and mostly are coded as “[course]-other” in the SCED list. Xu and Kelly split these SCED codes based on course title, grade taken, honors or other course classification (S. Xu, personal communication, December 16, 2021). Using SPSS syntax listed in Appendix A, the course code (T3SSCED) was used to categorize the 17,539 courses into the 10 course categories. The remaining 1,734 “[course]-other” courses were then inspected by their course title (T3SCRSNAM), credit type (T3SCRDTYP), student attributes (T3SATTIB, T3SATTAP, T3SATTHA, T3SATTCP, T3SATTCR, T3SATTCT), and grade taken (T3SGRLEV) to accurately assign a difficulty score (example code is provided in Appendix A).

In a true sense, the variable is ordinal in that the difference in difficulty between Algebra I and Geometry will not exactly correspond to the difficulty between Precalculus and Calculus. However, since there are a large number of categories, 10, the variable was treated and modeled as continuous. The full list of SCED math course codes and categorization can be found in Appendix B. Table 4 shows the frequency of the categorization for the highest math course taken for the study sample.
Table 4

Frequencies of Highest Math Course Taken

<table>
<thead>
<tr>
<th>Course categories</th>
<th>Black</th>
<th>Hispanic/Latinx</th>
<th>White</th>
<th>Combined Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>n</td>
<td>%</td>
<td>n</td>
<td>%</td>
</tr>
<tr>
<td>Less than Algebra 1</td>
<td>5</td>
<td>0.5</td>
<td>5</td>
<td>0.5</td>
</tr>
<tr>
<td>Algebra 1</td>
<td>41</td>
<td>4.4</td>
<td>41</td>
<td>4.4</td>
</tr>
<tr>
<td>Geometry</td>
<td>47</td>
<td>5.0</td>
<td>58</td>
<td>6.2</td>
</tr>
<tr>
<td>Transition</td>
<td>26</td>
<td>2.8</td>
<td>33</td>
<td>3.5</td>
</tr>
<tr>
<td>Algebra 2</td>
<td>156</td>
<td>16.6</td>
<td>168</td>
<td>17.8</td>
</tr>
<tr>
<td>Applied math elective</td>
<td>89</td>
<td>9.4</td>
<td>86</td>
<td>9.1</td>
</tr>
<tr>
<td>Algebra 3 or equal</td>
<td>90</td>
<td>9.6</td>
<td>64</td>
<td>6.8</td>
</tr>
<tr>
<td>Trigonometry or equal</td>
<td>354</td>
<td>37.6</td>
<td>306</td>
<td>32.5</td>
</tr>
<tr>
<td>Calculus or equal</td>
<td>127</td>
<td>13.5</td>
<td>161</td>
<td>17.1</td>
</tr>
<tr>
<td>Higher than Calculus</td>
<td>7</td>
<td>0.7</td>
<td>20</td>
<td>2.1</td>
</tr>
</tbody>
</table>

Additional Variables in the Analysis

**Weighting.** The HSLS:09 base-year and follow-up studies all include analytics weights. These weights are used to account for student, school, and/or parent non-responses (Ingles et al., 2011). The school-level weight (**W1SCHOOL**) was included in the level-two model to account for school non-response bias. The first-year base weight for schools is appropriate because the only variable included in the analysis for schools came from the base-year study. The student weight (**W3W1STUTR**) came from the 2013 update and transcript study. It was calculated with three nonresponse adjustments to account for nonresponse during the base-year and the 2013 update and also transcript nonresponse (Ingles et al., 2015). The variables primarily come from the base year and transcript study. Some demographic variables, X2SEX, X2RACE, and X4SES come from follow-ups studies. However, these variables were computed using base-year data, and if missing in the base year, were re-asked in later iterations (Ingles et al., 2013). Additional non-response bias weighting was unnecessary since data was only backfilled and no new
information was included. Since the student-level variables came from the base-year study and the transcript study, the W3W1STUTR analytic weight was used as the weight for analysis.

**Identification Variables.** The HSLS:09 data set included ID variables for both the student and the school. The student ID variable (STU_ID) was used across all data collections and was the unique student-level identifier. The school ID variable (SCH_ID) was used to nest students into their school.

**Data Analyses**

The analysis used three separate models to test the extent to which various factors impacted the outcome measure, highest math course taken during high school. The three racial/ethnic groups were modeled separately so that only students who identified as White were included in one model, those who identified as Black/African American were in a second model, and those who listed their ethnicity as Hispanic/Latinx, inclusive of all races, were included in the final model. This separation of models aligned with the analysis conducted by Anderson and Ward (2015) who looked at racial differences in the impact of motivational factors for high achieving students.

Preliminary analysis and descriptive statistics were conducted in IBM SPSS Version 22 and 28. The multilevel regression analysis was conducted using HLM 8.1, which is software specifically designed for multilevel modeling (Raudenbush & Congdon, 2021).

**Data Preparation, Preliminary Analysis, and Descriptive Statistics**

Data were examined for missingness, outliers, and then some variables/scales were recoded or transformed from their original measure in the data set as needed. Participants who did not identify as a member of one of the three selected racial/ethnic categories of interest were removed from the sample. Selecting these specific racial groups allows the racial and ethnic
groups who have been historically disenfranchised in STEM education to be compared to the current racial majority in the United States. Other disenfranchised groups like Pacific Islanders and Indigenous peoples of the Americas did not have a large enough sample size to meet multilevel modeling standards ($n = 159$) (Garrison, 2020). While students of Asian descent often experience racial bias, stereotyping, and microaggression in STEM education, this group of students remains over-represented in STEM fields in the United States and was not the focus of this study (Chen & Buell, 2018; Lee et al., 2020; McGee et al., 2016). Other studies investigating racial differences in educational, occupational, and child-related studies have focused on these three racial/ethnic groups (e.g., Anderson & Ward, 2013; Kospentaris & Stratton, 2021; Magnuson & Waldfogel, 2005; Melendez & Melendez, 2010; Shlay, 2010).

Additionally, any participants who had missing data or a nonresponse recorded on any of the measures included in the analysis were removed from the sample. To match how the scale scores are created in HSLS:09 the researcher first recoded, then conducted principal components analysis on the four constructs that make up STEM cost. This process was completed prior to removing any participants from the sample since the item weights could change with a smaller sample and the math attitude scales were created using the full HSLS sample. The variables associated with STEM expectations and sex were recoded as the final step before modeling.

**Multilevel Modeling**

Multilevel modeling was the appropriate statistical analysis to use due to the nested structure of the data. In educational data, students are often sampled from the same school or classroom creating nesting. Nested data structures violate the assumption of independence required by traditional statistical analyses (Peugh, 2010). When data is nested, multilevel modeling is the preferred method of analysis as it produces less biased estimations and standard
errors (Huang, 2018; Osborne, 2000). Additionally, MLM allows the researcher to ask more complex questions such as the impact of interactions effects which standard regression cannot do.

The data used in this study were considered hierarchical, since the students were clustered within a school. Additionally, the level-2 data (i.e., schools) were a randomized sample of all schools in the US in 2009. The “level-2 effect is called a ‘random effect,’” because the schools were randomly selected (Garson, 2019, p. 5). A random intercepts model was run using HLM 8.1, since there were level-1 and level-2 predictors hypothesized to impact the outcome variable, highest math course.

In the HLM 8.1 software, the school ID variable was the linking variable used to nest students within schools. Students were assigned a student-level analytic weight appropriate for use of transcript data with baseline data, while the schools received the school-level base weight. No adjustments were made to the HSLS-provided weights as the HLM software normalizes the weights at each level, so that they have a mean of 1.0 within each level (Raudenbush et al., 2019). Additionally, the software automatically scales the weights using the procedure described in Pfefferman et al. (1998) for weighting unequal probability of selection in multilevel models (Chantala et al., 2006).

**Model Building.** Several progressively complex models were fit to the data starting with the null model and ending at a well-fit model with student- and school-level predictors for some racial/ethnic groups. Each racial/ethnic model was run separately. To provide clarity throughout the results the models for Black students are referred to as Model B.Null, Model B.1, etc., the Hispanic/Latinx students’ models are denoted with an H, and the model for White students are denoted with a W.
The continuous variables in this study were grand-mean centered when added into the models. Grand-mean centering (GMC), where the mean score for each variable across all observations was subtracted from each observation and the new mean of each variable was zero, was used for all continuous variables. Centering did not change the variance of the variables or their correlation with the other variables (Kreft & Jan de Leeuw, 1998). Instead, the centered scores “represented a deviation from the mean” instead of its raw value meaning (Finch et al., 2019, p. 34). Grand-mean was chosen over group-mean centering, since the third research question specifically references variables at level-2.

**Null Model.** The null model was fit first. The purpose of the null model was to determine if the school grouping significantly impacted the highest math course taken in high school. A significant finding would indicate that multilevel modeling was necessary in order to appropriately account for the nested structure of the data. An intraclass coefficient (ICC) different from zero would indicate that multilevel modeling was necessary.

**Model 1.** The first conditional model was a random coefficients model which consisted of demographic and background student-level characteristics. Both sex and SES were included in the model along with prior academic achievement. The two academic achievement variables, eighth-grade math letter grade and ninth-grade math ability score, were included as base-level predictors. The binary variable, sex, had females (0) as the reference group. SES and math ability were entered using GMC.

**Model 2.** For the next level-1 conditional model, STEM expectancy-related factors were added first, due to the large number of motivational characteristics. Based on the SEVT framework and subsequent findings, expectancies often play a less direct role on choice than do the subjective task values and theoretically are more likely to be nonsignificant than value-
related factors (Eccles & Wigfield, 2020). Expectation of STEM occultation at age 30 (non-STEM field was the reference group, 0), math self-efficacy, and math identity were GMC in the first iteration. The researcher selected to run these as fixed effects since the research questions aim to address the impacts of the level-1 and -2 predictors on the outcome variable and are not specifically looking at how group clustering impacts the level-1 predictors. Retaining only the significant expectancy-related predictors, the value-related predictors were then added, math utility, math interest/attainment value, and STEM cost.

**Model 3.** The hypothesized final model consisted of school-level variables and was a random intercept ANCOVA model (Garrison, 2020). These factors included the percentage of students at the school who are eligible for free and reduced lunch as a proxy for school poverty levels, grand mean-centered in the model, the urbanicity of the school, dummy coded so that suburban is the reference, and the dichotomous variable of control which indicates if the school is public (0) or private (1). As outlined in the review of literature schools that have high poverty rates are often underfunded and under-resourced (Alderman, 2006; Oakes & Saunders, 2004; Xie et al., 2015). The hypothesis was that as schools' poverty levels increase, advanced math course-taking will decrease. Additionally, private schools often show higher math gains and more advanced course offerings. The continuous variable, poverty level, was entered first, followed by the ordinal and nominal variables.

**Model Comparisons.** In order to determine which model fit the data best, a number of criteria were used. First, the likelihood ratio test was conducted to determine which of the two models fit the data better. The likelihood ration test consists of comparing a “reduced” model within a “full” model, where the “reduced” model only contains a subset of parameters in the “full” model (Peugh, 2010). A chi-squared distribution was used where the degrees of freedom
was the difference in the number of parameters between the two models (Hox, 2010). Alpha was set at .05 to determine if one model showed a significant improvement over another. A non-significant finding indicated that the addition of more effects did not significantly reduce the error explained by the model, and so the more parsimonious model was retained (Garson, 2020).

As is common practice, additional information criteria measures were employed to make determinations about which model to retain. The Akaike Information Criteria (AIC) was examined first (Akaike, 1973). AIC is derived from the information theory framework and takes both the deviance score and the number of parameters into account (Hox, 2010; Hox & Roberts, 2011). Bayesian Information Criteria (BIC) on the other hand considers the deviance score and estimates the number of units at the highest level (Hox, 2010; Schwarz, 1978).

Both AIC and BIC allow model comparisons with non-nested models as long as both models use the same underlying data and sample (McCoach & Black, 2012). Smaller AIC and BIC values represented better fitting models. Both criteria are subject to bias and have penalties when increasing the number of parameters estimated. Garson summarized these limitations when they stated, “AIC risks choosing too large a model while BIC risks choosing too small a model” (2020, p. 125). An AIC difference of less than 10 and a BIC difference less than 2 do not provide strong enough evidence that one model better fit the data than another (Garson, 2020). This was the criterion used to evaluate models. The researcher employed a combination of model comparison approaches as suggested by McCoach and Black (2012). Likelihood ration tests, AIC, and BIC were all evaluated when selected the best fitting model.
Chapter 4: Results

This chapter presents the results of the model building process and is divided into sections based on each model: (a) Null model, (b) Model 1- consisting of background and demographic student factors, (c) Model 2- adding SEVT factors, and (d) Model 3- including school-level variables. Procedures and results for each racial/ethnic group and the overall findings are presented under each model.

Null Model

First, the unconditional models were fit with no predictors to determine whether there was a sufficient between-group variance to warrant a multilevel approach for each group. The highest math course taken, MATHCRS, was used as the outcome variable. Equation 1 represents the formula for the null model for all racial/ethnic groups.

\[ \text{MATHCRS}_{ij} = \gamma_{00} + u_{0j} + r_{ij} \] (1)

The results for Model B.Null indicated significant school-level variance (\( \tau_{00} = 1.52, p < .001 \)). Similarly, the results for the H.Null model and the W_Null model were both significant (\( \tau_{00} = 2.39, p < .001; \tau_{00} = 3.45, p < .001 \), respectively). This result indicated that there was significant between-school variability in the highest math course taken by students, and thus a multilevel approach was necessary (Raudenbush & Bryk, 2002; Wang et al., 2011). ICCs ranged from .35 to .51 (see Tables 5, 6, and 7) indicating that between 35% and 51% of the variance in the highest level of math course taken is explained by the school.

Model 1

Model 1 included main effects for sex, SES, math ability, and prior math achievement to answer Research Question 1—How do background characteristics and prior academic
experiences impact advanced math course-taking in high school? How do the impacts differ for Black, Latinx/Hispanic, and White students?

**Model B.1**

The model for Black students, Model B.1.1 was run with all the demographic variables. In the first iteration, sex ($p = .116$), a grade of D compared to a grade lower than a D ($p = .063$), and a grade of C compared to a grade lower than a D ($p = .093$) were all nonsignificant factors in predicting highest math course taken. This model showed a significant improvement in model fit compared to the B.Null model ($\chi^2 = 322.95, p < .001$). A second model was run Model B.1.2 to remove sex (Garson, 2019). Although eighth-grade math grades of D and C were both nonsignificant, they were retained in the model to account for the dummy coding with the ordinal variable. This model resulted in a grade of B, a grade of A, and ninth-grade math ability being significant factors, but SES ($p = .091$) did not significantly impact the highest math course taken for Black students. This model had better fit than Model B.1.1 ($\chi^2 = 33.13, p < .001$). A third iteration of the model was run, Model B.1.3, and contained only ninth-grade math ability and eighth-grade math grades. This model had significantly better fit than the previous model, B.1.2, ($\chi^2 = 11.82, p < .001$) and the null model, B.Null, ($\chi^2 = 278.00, p < .001$). Both AIC and BIC were reduced beyond the required threshold between the null model and Model B.1.3. Model B.1.3 was retained as the best level-1 model for background academic and demographic characteristics for Black students.

**Model W.1**

In the model for White students, Model W.1.1, all level-1 background demographic and academic variables were included. A number of factors were nonsignificant, though it was a better fitting model ($\chi^2 = 464.36, p < .001$). Sex ($p = .091$) and all eighth-grade math grade
dummy variables, grade of A ($p = .271$), grade of B ($p = .337$), grade of C ($p = .499$), and grade of D ($p = .699$) were all nonsignificant factors. A second model was run, Model W.1.2, that removed those factors and kept ninth-grade math ability and SES. This model produced better model fit compared to Model W.1.1 ($\chi^2_{5} = 12.08, p < .033$) and W.Null (reported in Table 6). There was an appropriate reduction for both AIC and BIC between W.1.2 and the W.Null model (see Table 6). Model W.1.2 was retained as the best model for background academic and demographic characteristics for White students.

**Model H.1**

The first conditional model for Hispanic/Latinx students, Model H.1.1 showed an improved model fit but contained nonsignificant predictors for sex ($p = .546$) and SES ($p = .337$). Only one of the dummy variables for grade, eighth-grade math grade of A was significant. The model was rerun to include only eighth-grade math grade and ninth-grade math ability. This model, H.1.2, reduced the AIC and BIC (see Table 7) and had superior fit indices compared to the null model, H. Null, ($\chi^2_{5} = 682.52, p < .001$). Model H.1.2 was kept as the best fitting model for background characteristics for Hispanic/Latinx students.

**Model 1 Results**

For Black and Hispanic/Latinx students for each one-point increase above their peers’ average score, they would show an increase of 0.07 in the highest math course taken. For White students, on the other hand, a one-point increase in their math ability above their peers equated to a 0.11 increase in the difficulty of their math course taken. The only group whose socioeconomic status impacted their high school math courses was White students. For each standard deviation increase in SES compared to their peers, White students saw a whole-point increase in their highest math course taken.
Hispanic/Latinx students who made an A in their eighth-grade math course were more likely to take a math course almost two levels higher ($\gamma = 1.63$) than their peers who made lower than a D in eighth grade. Similarly, Black students who made either an A or a B were more likely to take math courses two levels higher than their peers who made lower than a D in eighth grade ($\gamma = 2.11$ & $\gamma = 2.57$, $p > .001$, respectively). White students on the other hand did not significantly differ in their highest math course based on their previous performance in eighth grade.
### Table 5

**MLM Results for Black Students**

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>B Null Estimate (SE)</th>
<th>Model B.1 Estimate (SE)</th>
<th>Model B.2 Estimate (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>6.66 (.15) ***</td>
<td>4.79 (.50) ***</td>
<td>5.21 (.37) ***</td>
</tr>
<tr>
<td>8th grade math grade</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>2.11 (.59) ***</td>
<td>1.31 (.48) **</td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>2.57 (.63) ***</td>
<td>2.01 (.45) ***</td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>1.06 (.66)</td>
<td>1.09 (.52) *</td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>0.98 (.55)</td>
<td>1.15 (4.7) *</td>
<td></td>
</tr>
<tr>
<td>9th grade math ability †</td>
<td>0.07 (.01) ***</td>
<td>0.06 (.01) ***</td>
<td></td>
</tr>
<tr>
<td>Math identity ‡</td>
<td></td>
<td>0.51 (.12) ***</td>
<td></td>
</tr>
</tbody>
</table>

| Random Factors                |                      |                         |                         |
| Intercept                     | 1.52 (1.23) ***      | 1.29 (1.14) ***         | 1.14 (1.19) ***         |
| Level-1 error                 | 2.82 (1.68)          | 2.04 (1.43)             | 1.81 (1.34)             |

| Model Comparisons             |                      |                         |                         |
| Deviance/ -2LL                | 4148.13              | 3877.21                 | 3798.07                 |
| Model df                      | 3                    | 8                       | 9                       |
| Likelihood Ratio Test         |                      | 278.00 ***              | 72.06 ***               |
| df                            | 5                    |                         | 1                       |
| AIC                           | 4154.13              | 3893.21                 | 3816.07                 |
| BIC                           | 4166.40              | 3925.92                 | 3852.88                 |

| Statistics                    |                      |                         |                         |
| ICC                           | 0.35                 | 0.39                    | 0.44                    |
| Proportion of Variance Explained |                  |                         |                         |
| Level 1                       | 0.28                 | 0.36                    |                         |

Notes. * $p < .05$, ** $p < .01$, *** $p < .001$.

† GMC

‡ Grade “lower than a D” is the reference.
<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>W Null Estimate (SE)</th>
<th>Model W.1 Estimate (SE)</th>
<th>Model W.3 Estimate (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>6.29 (.37) ***</td>
<td>6.75 (.26) ***</td>
<td>7.43 (.20) ***</td>
</tr>
<tr>
<td>SES +</td>
<td>—</td>
<td>1.00 (.25) ***</td>
<td>0.95 (.24) ***</td>
</tr>
<tr>
<td>9th grade math ability +</td>
<td>—</td>
<td>0.11 (.02) ***</td>
<td>0.11 (.02) ***</td>
</tr>
<tr>
<td>Location</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>City b</td>
<td>—</td>
<td></td>
<td>—0.71 (.25) **</td>
</tr>
<tr>
<td>Rural b</td>
<td>—</td>
<td>—</td>
<td>-1.04 (.51) *</td>
</tr>
<tr>
<td>Town b</td>
<td>—</td>
<td>—</td>
<td>-0.37 (.39)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Random Effects</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>3.45 (1.86) ***</td>
<td>2.21 (1.48) ***</td>
<td>1.99 (1.41) ***</td>
</tr>
<tr>
<td>Level-1 error</td>
<td>3.13 (1.82)</td>
<td>2.03 (1.42)</td>
<td>2.03 (1.43)</td>
</tr>
</tbody>
</table>

| Model Comparisons |                      |                         |                         |
| Deviance/ -2LL    | 4520.55              | 4068.27                 | 4045.92                 |
| Model df          | 2                    | 4                       | 7                       |
| Likelihood Ratio Test | —                    | 452.28 ***         | 22.35 ***          |
| df              | —                    | 2                       | 3                       |
| AIC             | 4526.55              | 4078.27                 | 4061.92                 |
| BIC             | 4539.23              | 4099.40                 | 4095.73                 |

| Statistics      |                      |                         |                         |
| ICC             | 0.51                 | 0.52                    | 0.49                    |

| Proportion of Variance Explained |                      |                         |                         |
| Level 1                  | —                    | 0.39                    | 0.39                    |
| Level 2                  | —                    | —                       | 0.42                    |

Notes. * p < .05, ** p < .01, *** p < .001.

+ GCM

b Suburban location is the reference.
### Table 7

**MLM Results for Hispanic/Latinx Students**

<table>
<thead>
<tr>
<th></th>
<th>H Null Estimate (SE)</th>
<th>Model H.1 Estimate (SE)</th>
<th>Model H.3 Estimate (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fixed Effects</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>6.45 (.38) ***</td>
<td>5.88 (.31) ***</td>
<td>5.97 (.37) ***</td>
</tr>
<tr>
<td><em>8th</em> grade math grade</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A&lt;sup&gt;a&lt;/sup&gt;</td>
<td>—</td>
<td>1.63 (.44) ***</td>
<td>1.67 (.45) ***</td>
</tr>
<tr>
<td>B&lt;sup&gt;a&lt;/sup&gt;</td>
<td>—</td>
<td>0.30 (.38)</td>
<td>0.32 (.39)</td>
</tr>
<tr>
<td>C&lt;sup&gt;a&lt;/sup&gt;</td>
<td>—</td>
<td>–0.59 (.40)</td>
<td>–0.58 (.41)</td>
</tr>
<tr>
<td>D&lt;sup&gt;a&lt;/sup&gt;</td>
<td>—</td>
<td>–0.50 (.43)</td>
<td>–0.47 (.43)</td>
</tr>
<tr>
<td><em>9th</em> grade math ability&lt;sup&gt;d&lt;/sup&gt;</td>
<td>—</td>
<td>0.07 (.02) ***</td>
<td>0.06 (.02) ***</td>
</tr>
<tr>
<td><strong>Location</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>City&lt;sup&gt;b&lt;/sup&gt;</td>
<td>—</td>
<td>—</td>
<td>0.10 (.32)</td>
</tr>
<tr>
<td>Rural&lt;sup&gt;b&lt;/sup&gt;</td>
<td>—</td>
<td>—</td>
<td>–0.26 (.44)</td>
</tr>
<tr>
<td>Town&lt;sup&gt;b&lt;/sup&gt;</td>
<td>—</td>
<td>—</td>
<td>–1.00 (.44) *</td>
</tr>
<tr>
<td>Public vs. Private</td>
<td>—</td>
<td>—</td>
<td>0.80 (.27) **</td>
</tr>
<tr>
<td><strong>Random Effects</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>2.39 (1.55) ***</td>
<td>1.39 (1.12) ***</td>
<td>1.30 (1.14) ***</td>
</tr>
<tr>
<td>Level-1 error</td>
<td>3.52 (1.88)</td>
<td>1.66</td>
<td>1.62</td>
</tr>
</tbody>
</table>

**Model Comparisons**

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Deviance/ -2LL</td>
<td>4369.86</td>
<td>3687.34</td>
<td>3658.71</td>
</tr>
<tr>
<td>Model df</td>
<td>2</td>
<td>7</td>
<td>11</td>
</tr>
<tr>
<td>Likelihood Ratio Test</td>
<td>—</td>
<td>682.52 ***</td>
<td>28.63 ***</td>
</tr>
<tr>
<td>df</td>
<td>—</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>AIC</td>
<td>4375.86</td>
<td>3703.34</td>
<td>3682.71</td>
</tr>
<tr>
<td>BIC</td>
<td>4388.16</td>
<td>3736.14</td>
<td>3731.92</td>
</tr>
</tbody>
</table>

**Statistics**

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>ICC</td>
<td>0.40</td>
<td>0.46</td>
<td>0.44</td>
</tr>
<tr>
<td>Proportion of Variance Explained</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Level 1</td>
<td>—</td>
<td>0.53</td>
<td>0.54</td>
</tr>
<tr>
<td>Level 2</td>
<td>—</td>
<td>—</td>
<td>0.46</td>
</tr>
</tbody>
</table>

Notes: *p < .05, **p < .01, ***p < .001.

<sup>a</sup> GMC
<sup>d</sup> Grade “lower than a D” is the reference.
<sup>b</sup> Suburban location is the reference.
Model 2

After there was acceptable model fit for all three racial groups’ Model 1, the motivational characteristics were added as fixed effects to answer Research Question 2 — In what ways do student’s views of the value of mathematics and expectations for success in math during freshman year of high school influence high school advanced math course-taking for different racial groups?

Model B.2

For Black students, Model B.2.1 showed that STEM occupation at age 30 ($p = .255$) and math self-efficacy ($p = .838$) were nonsignificant predictors. Model B.2.2 was run with only eighth-grade math grade, ninth-grade math ability, and math identity as predictors. While this model’s goodness of fit test was not significantly better than Model B.2.1 ($\chi^2 = 4.79, p = .089$), the BIC was reduced by 7.39 points, compared to the required threshold of 2 points, indicating that the fit was slightly better (Garson, 2020). To maintain the same procedures of removing nonsignificant predictors from the model, Model B.2.3 included the three significant background and expectancy-related variables and added in the value-related factors. This model showed that math utility ($p = .083$), math interest ($p = .871$), and STEM cost ($p = .085$), all of the value-related factors, were not significant factors in influencing the highest math course taken for Black students. There was an acceptable reduction in both the AIC and BIC criteria between this model and Model B.1.2 (see Table 5). Once the value-related factors were removed Model B.2.2 remained the simplest, but best-fitting model, and is represented in Equation 2.

$$MATHCRS_{ij} = \gamma_{00} + \gamma_{10}*GR_D_{ij} + \gamma_{20}*GR_C_{ij} + \gamma_{30}*GR_B_{ij} + \gamma_{40}*GR_A_{ij}$$
$$+ \gamma_{50}*ABILITY_{ij} + \gamma_{60}*IDENTITY_{ij} + u_{0j} + r_{ij}$$  \(2\)
Model W.2

The second model for White students, Model W.2.1, was run and included the expectancy-related factors. None of the added predictors math self-efficacy ($p = .686$), math identity ($p = .543$), or STEM expectancies ($p = .157$) were significant, though the model was an improvement over Model W.1.2 ($\chi^2_3 = 16.72, p = .001$). The next model, Model W.2.2 was run to include SEVT values-related factors of math utility, math interest, and STEM cost. These factors were all nonsignificant and removed from the model, leaving no SEVT factors as significant impactors of the highest math course taken for White students.

Model H.2

Following the same procedures as the models for the two previous racial groups, expectancy-related factors were added first for the Hispanic/Latinx group in Model H.2.1. All three factors, self-efficacy ($p = .695$), STEM expectation ($p = .436$), and math identity ($p = .585$), were nonsignificant in influencing highest math course taken for Hispanic/Latinx. Removing those factors, the three value-related factors were then added to the model. Model H.2.2 showed similar results to the White student model with no value-related factors influencing the outcome variable, highest math course taken. Though the model fit was slightly better ($\chi^2_3 = 9.95, p = .019$), the AIC and BIC indices were not measurably reduced to indicate that this model should be retained over Model H.1.2.

Model 2 Results

Black students were the only group who were significantly impacted by their SEVT motivational factors. For that group only identity, how much they or others viewed them as a math person, was impactful. For this group for every two standard deviations above the average
math identity of their peers, students were likely to take a math course one level more difficult than their peers. White and Hispanic/Latinx students did not show any significant SEVT factors.

Originally, an additional model was proposed to test the interactions between significant demographic characteristics, like sex and SES, and the SEVT factors. However, no racial/ethnic group had significant factors in each of those categories, so no interactions were tested.

**Model 3**

To determine if the hypothesized relationships hold true and to answer Research Question 3—What school-level factors influence advanced math course-taking in high school, the researcher added in the level-two variables and then assessed model fit. A final model for each race was produced and the results analyzed in the discussion section.

**Model B.3**

The school-level variable for poverty level was added first for the Black student group. The chi-squared test of model fit did not indicate an improvement in the model compared to Model B.2.2 ($\chi^2_1 = 0.46, p > .500$), and the percentage of students eligible for free and reduced lunch was nonsignificant ($p = .654$). That variable was removed, and the ordinal variable, school location, and the dichotomous variable, school control, were then added. This model, Model B.3.2 attenuated the model fit and showed only the dummy variable, township, as significant ($p = .049$). A third model was run which removed school control only leaving school location. Model B.3.3 did not show improvement in overall model fit ($\chi^2_3 = 6.77, p = .078$), nor were any level-2 predictors significant. The more parsimonious model, Model B.2.2, was retained as the final model for explaining the highest math course taken during high school for Black students and is represented in Equation 2.
Model W.3

School-level factors were next added to the model for White students. Model W.3.1, which included school poverty levels, did not show a significant improvement over Model W.1.2 ($\chi^2_1 = 1.77, p = .180$), and poverty levels were nonsignificant in influencing highest math course taken ($p = .618$). Model W.3.2 was run next and included school location and school control. Two dummy variables, rural and city locations, were both significant school-level factors. The school control, public or private, was nonsignificant ($p = .452$). Model W.3.3 was rerun removing that factor and showed a significant improvement in model fit compared to Model W.1.2 ($\chi^2_3 = 22.35, p < .001$). The AIC and BIC criteria met the acceptable threshold for reduction indicating a better fitting model (see Table 6). Model W.3.2 was retained as the best fitting model for White students and is shown by Equation 3.

$$MATHCRS_{ij} = \gamma_{00} + \gamma_{01} \times LOC\_TOWN_j + \gamma_{02} \times LOC\_RURAL_j + \gamma_{03} \times LOC\_CITY_j + \gamma_{10} \times SES_{ij} + \gamma_{20} \times ABILITY_{ij} + u_{0j} + r_{ij}$$  \hspace{1cm} (3)

Model H.3

For Hispanic/Latinx students Model H.3.1 was run which added the proxy for school poverty levels, percent of students eligible for free and reduced lunch. School poverty level produced nonsignificant results ($p = .062$) and was removed from further models. Model H.3.2 was subsequently run and included school control and location. This model showed a significantly better fit compared to Model H.1.2 ($\chi^2_4 = 28.63, p < .001$). Table 7 shows that both AIC and BIC were reduced between the two models indicating a better fit. Equation 4 showed the best overall model for Hispanic/Latinx students, Model H.3.2, in explaining the factors that influence their highest math course taken during high school.
\[
MATHCRS_{ij} = \gamma_{00} + \gamma_{01}{*LOC\_TOWN}_{j} + \gamma_{02}{*LOC\_RURAL}_{j} + \gamma_{03}{*LOC\_CITY}_{j} + \\
\gamma_{04}{*CONTROL}_{j} + \gamma_{10}{*GR\_D}_{ij} + \gamma_{20}{*GR\_C}_{ij} + \gamma_{30}{*GR\_B}_{ij} + \\
\gamma_{40}{*GR\_A}_{ij} + \gamma_{50}{*ABILITY}_{ij} + u_0j + r_{ij}
\] (4)

**Model 3 Results**

Overall, only the model for White students and Hispanic/Latinx students showed school-level factors influencing the highest math course taken during high school. For both groups, the geographic location was an important factor. For the Hispanic/Latinx group coming from a town or rural school compared to a suburban had a negative impact on taking harder math courses while those attending city schools were more likely to take the more challenging courses. For White students though attending a suburban school gave them the best odds of taking higher math courses whereas coming from a rural area school resulted in the least challenging courses. Only for the Hispanic/Latinx group was attending a private school influential.
Chapter 5: Discussion

This study had three main objectives: 1) to determine what student-level factors influenced the highest math course taken, 2) what school-level factors were influential, and 3) to determine how racial or ethnic groups differ in those meaningful factors. The following sections will include a discussion of the study results, implications of the findings, the limitations inherent within the study, and considerations for future research.

Student Background Characteristic’s Impact on Highest Math Course Taken

Following extant literature, the first research question aimed to examine how students’ background characteristics influenced their math course-taking choices. Both academic and demographic characteristics are known to impact students’ educational attainment in secondary settings. However, this study found that academic background was a primary influencer across all racial groups, whereas demographic characteristics only influenced specific groups’ course-taking practices.

Demographic Characteristics

Past researchers found that students’ socioeconomic background often influences high school course-taking with students from more affluent families taking more advanced math courses (Burkman & Lee, 2003; Tyson, et al., 2007). This study found analogous results. Socioeconomic status was a factor in math course-taking choices, specifically for White students. White students who were one standard deviation above their White peers on SES were more likely to take harder math courses in high school. Disparate findings were shown for Black and Hispanic/Latinx students though, likely because each racial and ethnic group was analyzed separately, and it has been well documented that SES and racial/ethnic background are closely tied. In fact, only 10% of White and Asian children are likely to be living in poverty while the
rates for Blacks (31%) and Hispanic/Latinx (26%) are much higher, only compounding these groups’ disenfranchisement in education (de Brey et al, 2019). The lack of observable relationship between SES and high math course in this study may suggest an interaction between student race and their economic resources, but a clear conclusion is unlikely without further examination. Since students’ poverty rates are often dissimilar for racial/ethnic groups, the current findings suggest future studies that explore in-depth how the two factors work concomitantly to influence math course enrollment.

This study also sought to elucidate gender differences in math course-taking. Results from this study echo the more recent trend in math and STEM education that women and girls’ academic choices during high school are more and more similar to their male peers (IES, 2011). Across all racial/ethnic groups, gender was not a significant factor for math course-taking practices. Although educational research is finding fewer gender differences in performance, ability, and choice in high school, gender disparities remain a common finding in educational studies and continue to plague STEM outcomes in college and careers (Justman & Méndez, 2018; Meinck & Brese, 2019).

*Academic Performance and Ability*

Academic performance and ability are often strongly tied to educational outcomes across all subject areas. Past studies suggest that prior performance in math, specifically during eighth grade, is a strong predictor of future math performance and course enrollment decisions during high school (Attewell & Domina, 2008; Burkman & Lee, 2003). This study found that for Black and Latinx/Hispanic students their performance in grade eight was indicative of their highest math course in high school. For Black students making any grade equal to a D or higher significantly impacted their future course enrollment. Black students making an A or a B were
even more likely to take higher math courses compared to Black students who made lower than a D in their eighth-grade math course. Hispanic/Latinx students showed similar though less pronounced differences in course enrollment based on their middle school grades. For this population making an A in math during eighth grade resulted in taking a course one or even two levels higher than their peers. Making anything less than an A was not a significant predictor of taking harder math later in school. These results highlight the importance of middle grades math on future math choices, specifically for minority students in the United States.

Ninth-grade math ability was examined to determine if it significantly influenced math course choices throughout high school. Eccles and Wigfield’s SEVT model (2020) highlights the cyclical nature of past performance as indicative of future choice and performance. Past studies have confirmed that mathematical achievement in ninth grade is a strong predictor of future choice and performance later in high school (Attewell & Domina, 2008; Burman & Lee, 2003; Hsieh et al., 2021). The results from this study echoed these previous findings. Regardless of race, all models in this study showed that as ninth-grade math achievement increased relative to their peers so did the student’s math-course difficulty at the end of high school.

One explanation for this phenomenon is that many schools use student course tracking to streamline curriculum planning and delivery. Tracking also called ability-grouping, “refers to any school organization structure that increases the homogeneity of instructional groups by stratifying students by curriculum standards, educational career goals, or ability” (Werblow et al., 2013, p. 270). Tracking is often used in math where similar ability students are grouped and placed on certain course tracks, e.g., remedial math, Algebra I in eighth grade, honors, etc. (Gamoran, 2010). Once a student is placed on a track, they often will continue taking subsequent courses in their track and not shift to a different track. If they do move, it is often down a track
(Irizarry, 2021; Spielhagen, 2006). This tracking means that high-ability students in ninth grade are more often placed on more advanced math tracks and are subsequently able to enroll in advanced courses throughout high school. Conversely, students who do not take Algebra I until 10th grade are simply unable to take all of the prerequisite courses to enter calculus in high school regardless of their desire to do so.

This tracking based on ability and the gatekeeping nature of Algebra I have been well documented to impact the number and rigor of advanced courses taken in high school and beyond (Champion & Mesa, 2018; Ngo & Velsaquez, 2020; Torbey et al., 2020). Recent research using the HSLS:09 data revealed racial differences in math track were not fully explained by ninth-grade math ability, and Black and Latinx students were more likely than their White peers to move down tracks (Gamoran, 2021; Irizarry, 2021). These findings, along with the results from this study, showcase the importance of both race and ability in looking at the trajectory of students’ math enrollment and the need to account for tracking during middle and high school.

Influences of Expectations and Values

The second research question focused on the factors used in Eccles’s and Wigfield’s Situated Expectancy Value Theory (2020). It asked how students’ views of the value of mathematics and expectations for success in math during freshman year of high school influenced advanced math course-taking for different racial groups. Mathematical ability beliefs are strongly tied to the choice to take advanced math. Students who have higher math self-concept perform better and opt to take these courses more frequently than their peers (Safavian, 2019; Simpkins & Davis-Kean, 2005; Suárez-Álvarez, 2014). Prior research shows that students with high academic self-concept and confidence in their math abilities are more likely to enroll
in STEM fields (Moakler & Kim, 2014). Other research has highlighted the importance of academic and mathematical identity for students’ course choices during high school. Students who see themselves as a math person perform better, are more likely to take advanced math and pursue STEM-related fields at higher rates (Flowers III & Banda, 2019; Jackson et al., 2020).

This study found that across all racial groups self-efficacy and expectations did not significantly influence math course enrollment. In fact, only for Black students were any of the expectancy factors significant. For Black students, an increase in mathematical identity was related to taking more advanced math by the end of high school. This finding mirrors prior research that shows that math identity is an important factor for Black students (Flowers III & Banda, 2019). Students develop their mathematical identity over time, but racial minority students develop math identity alongside their racial identity. For Black students, specifically, racial identity is inextricably tied to mathematical identity (Martin, 2007). This group of students often faces stereotype-threat in math courses and find that high attainment in math often separates them from their same-race peers and their racial identity (Ployhart et al., 2003; Venzant Chambers & Huggins, 2014). The findings from this study highlight the importance of math identity for Black students, but not for White or Latinx/Hispanic students. This is likely because Black students must have a high math identity to outweigh the “racial opportunity cost when enrolling in advanced courses frequently composed of mostly White and Asian students” (Kotok, 2017, p. 187; Venzant Chambers et al., 2014).

The lack of significant findings regarding self-efficacy, STEM expectations, and identity for White and Latinx/Hispanic students was not surprising since research has shown that expectancies are often less related to choice than subjective task values (Eccles & Wigfield, 2020). It is important for practitioners to understand that math identity development likely will
have differing impacts based on race/ethnicity for their students and could be most impactful for Black students. Although self-efficacy and STEM expectations did not significantly impact course enrollment for any student, they remain salient in discussions around math achievement and choice.

Prior studies suggest that utility, interest, cost, and attainment value often play a vital role in students’ math-related choices in school. Prior research showed that interest in STEM and math, in particular, is a driving force in students’ STEM choices (Ainley & Ainley, 2011; Regan & DeWitt, 2015). Additionally, research has suggested that subject-task values, like attainment and utility, increase math participation, achievement, and choice (Ball et al., 2017; Maltese & Tai, 2011; Wyatt et al., 2006). However, this study found disparate results. For each racial/ethnic group, having more positive beliefs about the value of math did not result in any significant difference in math course-taking during high school.

One explanation for the lack of significant findings on how motivational factors impact students’ course-enrollments could be the impact of tracking discussed earlier. By high school, students are often already on a course track with little room to move up, regardless of their expectations, interest, or values. As noted earlier, students who take Algebra I later are already at a disadvantage since the required course progression limits their ability to take more advanced math courses. They often have not been introduced to the same topics and as a result, score lower on math achievement tests (Smith, 1996).

Another reason that this study could have nonsignificant findings is that measuring affective beliefs starting in high school might actually be too late. Students’ beliefs become more rigid as they age and progress through school (Cleary & Chen, 2009; Ing & Nylund-Gibson, 2017). This relative stability in beliefs by high school could indicate that these factors are
working in the elementary and middle grades to predict student achievement. In fact, Petersen and Hyde (2015) found that students’ math self-concept in fifth grade was predictive of ninth-grade math performance. As the results showed student achievement and performance in eighth and ninth grade influence the students’ highest math course taken. It stands to reason that investigating how SEVT factors influence eighth and ninth-grade achievement and performance could show significant relationships and might also explain variance in course taking at the end of high school.

Whereas this study did not show any significant findings during the high school years for White or Hispanic/Latinx students and only a single significant finding, identity, for Black students, future research should not wholly dismiss the impact of SEVT factors. Many studies have tested the SEVT factors on math performance and choice and found partial support for the framework (e.g., Howard et al., 2019; Maltese, 2010; Petersen & Hyde, 2015; Safavian, 2019). Considering that this study found significant power in the influence of middle and early high school achievement and performance, it could underscore the importance of creating positive affective math beliefs in early and middle grades.

**School-level Impacts**

The third research question address the schoolwide impacts on students’ math course-taking. Previous literature has shown that school resources and funding can limit students’ opportunity to take more advanced courses (Alderman, 2006; Caldas & Bankston, 1997; Kastberg et al., 2016; Oakes & Saunders, 2004). When schools lack funding, which is often tied to the economic wealth of their surrounding communities, they are not able to provide access to quality curriculum at numerous levels, often resulting in high-poverty schools attaining lower academic outcomes only further compounding educational disparity between the poor and the
wealthy. The results from this study did not show a significant difference in school poverty levels, as measured by the number of students eligible for free and reduced lunch, to impact the highest math course a student took during high school. One explanation for this could have been that students from different racial/ethnic groups are more often clustered at schools with similar poverty rates, so separating models by race could mask the potential impact of school poverty (Hussar et al., 2020). Research has shown that schools that are primarily African American have lower student achievement above what can be accounted for by the individual effect of SES or race (Borman & Dowling, 2010). Primarily Black or Hispanic/Latinx schools often have higher poverty rates where even middle-class minority students are more likely to attend poor schools than poor White students (Reardon, 2016; Reardon et al., 2015; Saporito & Sohoni, 2007). This study showed that there was a 4- to 8-point difference in schools’ mean poverty rates between the racial/ethnic groups affirming the potential masking effect. Although this study did not support that school’s socio-economic status significantly impacted the highest-math course, investigating this relationship in the context of the school’s racial makeup could provide additional insights into school-level impacts. Also, the results in this study do not mean that school poverty does not impact students’ education; rather, they may imply the potential confounding of effect when race is modeled separately as is common in educational research (e.g., Jackson et al., 2021; Safavian, 2019). Future research into this complex relationship is encouraged.

Another school characteristic that previous research suggests influences students’ educational accomplishments and experiences is whether the school is public or private. Private schools show small though significant achievement gains for their students and sometimes offer more advanced math courses in high school (Egalite & Wolf, 2016; Xu & Kelly, 2020). Roughly
10% of elementary and secondary students in the United States attend private schools so this disparity does impact a measurable portion of students (Hussar et al., 2020). The results from this study found that the school sector, private or public, only impacted Hispanic/Latinx students. For this population going to a private school put them at an advantage compared to their Hispanic/Latinx peers attending public schools. For Black and White students, the type of school they attended did not influence their highest math course taken during high school. These findings suggest that the school sector is an important piece of the STEM attainment research, but those interactions with a student’s race must also be examined to differentiate the impacts for different racial groups.

Schools often mirror the communities which they serve. Previous research suggests that urban schools often have the lowest achievement and highest concentration of poverty (Burdick-Will & Logan, 2017). ACT scores are highest among suburban students followed by students from rural communities and lastly students from urban schools (Hopkins, 2005). However, other researchers did not find substantial evidence to confirm that schools’ geographic locations were impacting the math course tracks and highest math courses offered (Cogan et al., 2001). The results from this study, though, show that for White and Hispanic/Latinx students where their school is located is a significant influencer on math course enrollment. Interestingly, for Hispanic/Latinx students, schools in townships negatively impacted students taking advanced math courses as compared to a suburban school, while for White students attending a rural or city school compared to a suburban school showed a negative impact. This study highlights the importance of accounting for differences in schools’ geographic location because coming from a suburban school will likely benefit students more when it comes to preparing students for college STEM fields.
Past studies show that school characteristics often impact the students they serve. These characteristics often cluster around the concentrations of racial groups that make up the school. The results from this study add to the literature to show that school factors like private or public and geographic location do affect students’ math course enrollment. Other factors like school poverty could be masked when modeling racial groups separately or by not accounting for the racial/ethnic makeup of the school.

**Implications**

The results from this study provide both practical and theoretical implications. First, theoretical implications will be discussed as they pertain to SEVT’s influence on students’ academic choices and performance. Secondly, the practical implications of the study will be addressed as they relate to actions taken by both students and their families and the policymakers at the state and national levels.

**Theoretical Implications**

The results from this study provide insight into the nuances of students’ math-related choices. The findings suggest that motivational factors like self-efficacy, interest, cost, and utility-value may not play as prominent a role in students’ choices as school and background characteristics. More research is needed in order to determine if these mutable factors can overcome the rigid structure of student-tracking often used by many districts across the United States.

Secondly, students’ prior performance is modeled in the SEVT theory but is often not a prominent focus. Students who enter high school better prepared for rigorous math coursework are the students who end up taking higher math courses than their peers. The findings from this study show that high school might be too late to begin making a focused effort to develop
students’ mathematical affective beliefs. Looking at how past choices and values in elementary and middle school shaped students’ choices and performance entering high school could provide additional context when examining their high school math choices. While elementary students with more positive attitudes toward math are more likely to continue to view math positively, their views are much more malleable in elementary and middle school compared to high school (Cleary & Chen, 2009; Ing & Nylund-Gibson, 2017). This malleability provides a rich environment for interventions to increase mathematical beliefs and then examine how those changes can go on to impact high school that course-taking. This notion echoes Eccles and Wigfield (2020) suggestion that more research is needed on the “across time” portion of the SEVT model.

**Practical Implications**

The findings from this study highlight the importance of a strong mathematical foundation in elementary and middle grades. Across all racial and ethnic groups examined, students’ mathematical ability when entering high school impacted their highest math course taken by the end of their secondary years. Teachers and parents must continue to make a concerted effort to make sure that students are staying on grade level in mathematical reasoning and numeracy skills in the elementary and middle grades. As students move through their math curriculum in these early grades, it is imperative that students not fall behind. Falling behind will put students at a stark disadvantage not only in their mathematical content knowledge but also put them at risk of being placed on a lower math track for high school.

Even young students are accountable for the effort they put forth during the middle grades. As this study and many others have shown, the grade a student receives in math in eighth grade will impact their math trajectory in high school and in turn in college (Attewell & Domina,
It is documented that math scores in late elementary and early middle school (i.e., sixth and seventh grade) also play a vital role in influencing student academic attainment in high school (Balfanz et al., 2007; Siegler et al., 2012). Attending to these differences early could prove impactful for students’ math trajectories. Additionally, teachers should highlight the impact of their effort in eighth grade and explain to students the impact it could have on their future choices, opportunities, and even earnings into adulthood.

Students cannot change their schools’ geographic region, resources, or funding, and likely have little control over the choice between private and public. That leaves policymakers to correct disparities between opportunities afforded to children based on the schools they attend. Rural and urban elementary and secondary schools should strive to provide the same course offerings as suburban schools and seek funding to achieve this goal. National and state departments of education should continue to examine how disenfranchised students often suffer compounded negative effects by attending high poverty, low achieving schools and work to set policies that would alleviate divergent funding paths.

Limitations and Future Research

Since separate models were run for each race and the predictor variables for one race were removed due to non-significance and/or model fit in other models, direct comparisons were not strictly possible. Instead, general comparisons across races were analyzed. Additionally, the subsample for White students is much larger than for Latinx/Hispanic and Black/African American students. However, this was a relatively accurate representation of the U.S. population were in the HSLS data as 10.4% were Black/African American and 15.4% identified as Hispanic/Latinx, compared to the 2010 Census numbers that showed Blacks comprised 13% of the population and Hispanic/Latinx people 16% of the population (Humes et al., 2011).
combat this difference in group size a random selection of students was drawn to not exceed 2,000 for each racial group. Although there was a reduced sample size, this was at level 1. In multilevel modeling, it is more important to have a larger level-2 sample than level-1 (Maas & Hox, 2005).

Another limitation the researcher encountered was in the estimation method used. Though previous versions of the HLM software included an option to run two-level cross-sectional models with restricted maximum likelihood (REML) method, HLM8.1 did not include this feature (M. de Toit, private communications, January 26, 2022). Since there was a somewhat unbalanced design in the level-2 sampling, REML would have been better able to counteract the imbalance compared to full maximum likelihood.

The underlying transcript data also caused some possible limitations with the analysis. The SCED codes that high schools assigned to the courses were used, but inconsistencies at the high school coding level were present within the data. For example, one course titled “Trigonometry/Pre-Calculus” was given a SCED code of 02107, which equated to Algebra 3 or equal (code 7), at one school while another coded the identically titled course as 02110, which equated to Trigonometry or equal (code 8). Both the HSLS:09 research team (Ingles et al., 2015) and Xu and Kelley (2020) use the SCED codes without correction though and the same approach was taken for this study.

The Situated Expectancy Value items used in HSLS:09 could also have caused some issues. A recent dissertation by Webb (2020) found that some of the items created by the HSLS team had validity issues. The underlying items used to make the scale scores reference students’ ninth-grade math course, i.e., “How much do you agree or disagree with the following statements about your [fall 2009 math] course? What students learn in this course will be useful for a future
career.” (Ingles et al., 2013). This wording means that a student taking geometry was rating how useful geometry was while a student in business math was rating that specific course’s usefulness. This disparity in course specification could impact a student’s overall rating on one of the SEVT factors and future research should attend to those course differences.

In addition to the suggestions made in the previous discussion, one area of future study might look at when students took Algebra I to examine if students are hindered more by their math course track or instead by their motivation and desire to enroll in more and harder math courses. If students who have access to and take Algebra I earlier, such as in middle school, are pursuing math at higher rates than equally talented students without access, then the focus would be at the school and district level to enact change.

**Conclusion**

This study sought to elucidate the specific factors that impact high school math taking. The results show that students’ high school math course-taking decisions are often a result of their math ability when they enter high school regardless of their racial or ethnic background. Other factors outside of their control, like their school’s location or sector, also shape their course-taking trajectory. The only things within the control of the student are how they perform in their eighth-grade math course and, for Black students, how much or little they view themselves as a math person. K–12 policy must focus on increasing resources in the younger grades to give students the best possible opportunities to take advanced math in high school and prepare them for STEM careers in the future.
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Appendix A- SCED Recoding SPSS Syntax

***Recoding by SCED codes based on Xu and Kelley, 2020***.
RECODE T3SSCED ('02001'=1) ('02002'=1) ('02003'=1) ('02028'=0) ('02029'=0) ('02030'=0) ('02031'=0) ('02032'=0) ('02033'=0) ('02034'=0) ('02035'=0) ('02036'=0) ('02037'=0) ('02038'=0) ('02039'=0) ('02047'=1) ('02049'=1) ('02051'=1) ('02052'=2) ('02053'=2) ('02054'=2) ('02055'=4) ('02056'=5) ('02057'=7) ('02062'=0) ('02063'=0) ('02064'=0) ('02065'=0) ('02069'=88) ('02071'=1) ('02072'=3) ('02073'=6) ('02074'=6) ('02075'=3) ('02079'=3) ('02101'=7) ('02102'=9) ('02103'=8) ('02104'=8) ('02105'=8) ('02106'=8) ('02107'=7) ('02108'=8) ('02109'=8) ('02110'=8) ('02111'=9) ('02112'=9) ('02113'=9) ('02121'=9) ('02122'=10) ('02123'=10) ('02124'=9) ('02125'=10) ('02126'=9) ('02131'=8) ('02132'=8) ('02134'=8) ('02135'=7) ('02136'=0) ('02137'=0) ('02138'=0) ('02141'=7) ('02149'=7) ('02151'=4) ('02152'=4) ('02153'=6) ('02154'=6) ('02155'=6) ('02156'=4) ('02157'=1) ('02201'=7) ('02202'=7) ('02203'=9) ('02204'=6) ('02205'=0) ('02207'=0) ('02209'=88) ('02991'=1) ('02993'=6) ('02994'=88) ('02995'=88) ('02996'=88) ('02997'=6) ('02998'=5) ('02999'=88) ('0261'=88) (ELSE=-99) INTO Math_Course_Category.
VARIABLE LABELS Math_Course_Category 'Variables Name'.
EXECUTE.

***Examples of recoding by SCED codes based on course title***.
RECODE T3SCRSNAM ('Accel Math I'=2) ('Advanced Algebra 135'=2) ('Algebra 1 Support Concepts'=2) ('Algebra I AC'=2) ('Algebra I Lab'=2) ('ALGEBRA I-A'=2) ('ALGEBRA I-B'=2) ('Intermediate Algebra 1'=2) ('Accelerated Algebra Lab'=2) ('ALGEBRA I'=2) ('ALGEBRA 1-2'=2) ('Algebra Foundations'=2) ('Algebra I Interactions'=2) ('ADV ALGEBRA A'=2) ('ALGEBRA Enrichment'=2) ('Algebra I with Math Lab'=2) ('MATH FOUNDATIONS I'=1) ('MATH LAB ECA'=1) ('Math Tech 1'=1) ('Math Workshop 11'=1) ('MATHEMATICS INTERVENTION - III'=1) ('OCS INTRODUCTION TO MATHEMATICS'=1) ('SE MATH'=1) ('Step Up to High School Math sem. 1'=1) ('STUDY SKILLS (NJ)=1) ('TAKS Math Prep'=1) ('TUTORIAL ALGEBRA I'=1) ('Algebra Lab'=1) ('INTEGRATED MATHEMATICS I'=1) ('MATH ASSIST'=1) ('Math for Future 1'=1) ('MATH MAT 1'=1) ('MATH MATT2'=1) ('Honors Math Topics 5'=5) ('Honors Math Topics 6'=6) ('PRECOLLEGIATE MATH'=6) ('MATH COLL. READINES'=6) ('MATH COLLEGE READINESS'=6) ('MATH FOR COLLEGE READINESS - SEMESTER 1'=6) ('MATH FOR COLLEGE READINESS - SEMESTER 2'=6) ('MATH FOR COLLEGE READINES'=6) ('MATH FOR COLLEGE READINESS HONORS'=6) ('Math for College Readiness'=6) ('Math Coll. Readiness'=6) ('HSPA (Math) 3 Lab'=1) ('Math Istep'=1) INTO Revised_Math_Category_codes.
EXECUTE.

***Examples of recoding SCED codes by course title and school code***.
If (SCH_ID = '1316' AND T3SCRSNAM = 'Math Topics 5') Revised_Math_Category_codes =5.
If (SCH_ID = '1316' AND T3SCRSNAM = 'Math Topics 6') Revised_Math_Category_codes =5.
If (SCH_ID = '1316' AND T3SCRSNAM = 'Math Topics 1') Revised_Math_Category_codes =2.
If (SCH_ID = '1316' AND T3SCRSNAM = 'Math Topics 2') Revised_Math_Category_codes =2.
If (SCH_ID = '1316' AND T3SCRSNAM = 'Math Topics 3') Revised_Math_Category_codes =4.
If (SCH_ID = '1316' AND T3SCRSNAM = 'Math Topics 4') Revised_Math_Category_codes =4.
If (SCH_ID = '1316' AND T3SCRSNAM = 'Honors Math Topics 1')
    Revised_Math_Category_codes =2.
If (SCH_ID = '1316' AND T3SCRSNAM = 'Honors Math Topics 2')
    Revised_Math_Category_codes =2.
If (SCH_ID = '1316' AND T3SCRSNAM = 'Honors Math Topics 3')
    Revised_Math_Category_codes =4.
If (SCH_ID = '1855' AND T3SCRSNAM = 'Advanced Algebra')
    Revised_Math_Category_codes =2.
If (SCH_ID = '1859' AND T3SCRSNAM = 'MATH SEMINAR')
    Revised_Math_Category_codes =1.
If (SCH_ID = '1870' AND T3SCRSNAM = 'Math I H') Revised_Math_Category_codes =1.
If (SCH_ID = '1871' AND T3SCRSNAM = 'MATHEMATICAL MODELS')
    Revised_Math_Category_codes =8.
If (SCH_ID = '1897' AND T3SCRSNAM = 'College Entrance Math')
    Revised_Math_Category_codes =6.
If (SCH_ID = '1897' AND T3SCRSNAM = 'R/S COL ALGEBRA')
    Revised_Math_Category_codes =7.
### Appendix B- SCED Code Categorization

**Table 8**

*SCED Codes and the Corresponding Categorization*

<table>
<thead>
<tr>
<th>Course Name</th>
<th>SCED Code</th>
<th>Code</th>
<th>Course Name</th>
<th>SCED Code</th>
<th>Code</th>
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<tbody>
<tr>
<td>Informal Mathematics</td>
<td>02001</td>
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<td>Mathematic Analysis/Analytic Geometry</td>
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<td>Elementary Functions</td>
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<td>no obs</td>
<td>Linear Algebra</td>
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<td>Mathematics (Pre-k)</td>
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<td>Linear Programming</td>
<td>02112</td>
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<td>IB Further Mathematics—HL</td>
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<td>Foundation Mathematics—Independent Study</td>
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<td>IB Mathematics, Middle Years Program</td>
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<td>Foundation Mathematics—Other</td>
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<td>Inferential Probability and Statistics</td>
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<td>Number Theory</td>
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<td>Mathematics—Independent Study</td>
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<td>Mathematics—Workplace Experience</td>
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</table>

Dep. = coding depends on the course title, level, grade taken etc.
No obs = The SCED code was not present in the transcripts reviewed and was not categorized.
\(^1\) Some courses that have a specific SCED code such as Integrated Math I, II, III, IV did not use that SCED code in the transcripts compiled for HSLS:09, but those course titles were sued with SCED codes like 02999 “Math—Other.”
Appendix C - IRB Approval

The data used in this study was covered under University of Memphis IRB# PRO-FY2022-125.