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The Power of Preparation: How Rigorous High School Courses Relate to ACT Composite Scores

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Conclusions

The study finds that rigorous high school coursework—particularly in mathematics and science—is strongly associated with higher ACT® Composite scores. Students who completed advanced courses and studied subjects beyond foundational levels (e.g., math beyond Algebra II, science including biology, chemistry, and physics) consistently outperformed peers with less rigorous preparation. While machine learning models offered slight improvements in predictive accuracy over traditional regression methods, the study found that hierarchical linear models remained highly effective and more interpretable for educational research.

So What?

This study matters because it provides compelling evidence that rigorous high school coursework—especially in math and science—not only boosts ACT scores but also deepens our understanding of educational equity. While advanced coursework benefits all students, the gains are disproportionately higher for White, Asian, and higher-income students, revealing persistent gaps tied to race, gender, and socioeconomic status. These findings underscore the need for targeted interventions and support systems to ensure that all students can fully benefit from rigorous academic preparation.

Now What?

The implications of this study are clear: Schools and policymakers must prioritize expanding access to rigorous coursework—especially in math and science—to improve college readiness and ACT performance. However, simply offering advanced courses is not enough. The study shows that demographic disparities persist, meaning that targeted supports are essential to ensure all students benefit equally.

About the Authors

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Dr. Sanchez is a principal research scientist at ACT, where he studies postsecondary admissions, national testing programs, test preparation efficacy, and intervention effectiveness. Throughout his career, Dr. Sanchez has focused both on studying the transition between high school and college and on supporting the decision-making capacity of students and their families, as well as that of college administrators. His research has been widely cited in academic literature and by the media, including *The Wall Street Journal*, *The Washington Post*, *USA Today*, and the education trade press.

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Introduction

Concerns about the efficacy of a high school education for preparing students for postsecondary success have been an important topic in educational reform since the late 20th century. Pivotal reports such as *A Nation at Risk* and *The Condition of Education 2019* highlighted areas where American high schools were not meeting expectations, prompting stricter graduation requirements and an even greater emphasis on rigorous academic coursework (National Commission on Excellence in Education, 1983; McFarland et al., 2019). The result is a need for not only increasing the quantity of courses taken but also ensuring the quality of preparation in core academic areas such as mathematics and science. Since the demand for technological literacy and STEM-related skills continues to grow, these concerns are even more salient today.

Standardized college entrance exams like the ACT have been an essential part of assessing students' college readiness for many years. The relationship between high school coursework, particularly in math and science, and ACT performance has been the focus of much research. Noble and McNabb's (1989) foundational research shed light on how coursework and academic performance influence ACT outcomes. This research underscored that a strong high school curriculum, especially in STEM subjects, contributes significantly to the success of students on college entrance exams. That said, the educational landscape has changed considerably since the late 1980s, often driven by reforms like the adoption of Common Core standards and the integration of advanced technologies into teaching methodology. These shifts necessitate an update to previous research using modern statistical methods and data from more recent cohorts so we can better understand how student-level characteristics influence postsecondary success.

Radunzel and Noble (2012) noted the strong relationship between rigorous high school coursework and college entrance exam performance. This study showed that students who took more challenging courses in high school not only performed better on the ACT but also were more likely to succeed in college. This research particularly highlights the predictive power of academic rigor, reinforcing the notion that high school preparation serves a critical role in preparing students for both standardized test performance and long-term educational achievement. Additional research by Laing et al. (1987) and Harwell et al. (2016) provides strong evidence that taking additional math and science courses, particularly advanced courses, leads to higher ACT scores. Laing et al. (1987) found that increased course-taking in specific subject areas had the strongest effects on ACT performance in math and science. Similarly, Harwell et al. (2016) showed that students who completed at least three years of high school math, including advanced courses, were more likely to meet the ACT College Readiness Benchmark in math. Schiel et al. (1996) and Noble et al. (1999) illustrated that even when studies controlled for prior academic achievement, those students who enrolled in advanced math and science courses achieved significantly higher ACT scores. Furthermore, these trends were consistent across high schools around the country, suggesting that the benefits of rigorous coursework extend to a multitude of high school contexts.

Test performance, however, does not happen in a vacuum. McNeish et al. (2015) provided insight into the multidimensional nature of college readiness, emphasizing how important it is to consider both student-level and school-level characteristics. For example, while high school GPA (HSGPA) accounted for the greatest amount of variance in ACT Composite scores, noncognitive factors accounted for, at most, 4% of additional variance. This study illustrates the complex relationships among individual academic preparation, noncognitive factors, and other institutional factors, offering a comprehensive framework for understanding standardized test outcomes.

Educational outcomes such as standardized test performance have been shown to be impacted by demographic factors such as race, family income, and gender. The differences between these demographics contribute to gaps in senior year mathematics achievement test scores, which itself reflects a broader systemic barrier faced by underrepresented groups in education (Riegle-Crumb & Grodsky, 2010).

Advances in statistical methodologies have the potential to offer new opportunities in examining the relationships between coursework, demographic factors, and ACT performance. Traditional regression models can more effectively model group nesting through hierarchical, or mixed, modeling techniques. Hierarchical modeling is particularly well suited for educational research because it accounts for the nested structure of students within schools and therefore provides a more nuanced analysis of both individual and institutional influences on educational outcomes (Raudenbush & Bryk, 2002). Additionally, machine learning techniques like gradient-boosted machines present new opportunities for analyzing and exploring traditional educational research questions. Machine learning approaches bring additional advantages in that they can identify nonlinear relationships and complex interactions that traditional regression models may overlook.

Gradient-boosted machine models (GBM models) are a powerful tool for performing regression and classification tasks. GBM models build an ensemble of decision trees, with each tree correcting errors from previous ones until performance improves or a set number of trees is reached. Advantages include higher accuracy, the ability to handle complex data, the ability to identify feature importance, and versatility in various applications. GBM models combine multiple weak models into a strong model, focus on residuals for better performance, and can handle nonlinear relationships efficiently.

This study aims to expand upon the research by Noble and McNabb (1989) by providing a current analysis of how high school mathematics and science coursework is related to ACT performance. I focus on mathematics and science due to their progressively rigorous and sequential nature, unlike social studies or English. However, to account for factors related to motivation and preparation associated with advanced course-taking, I considered advanced coursework in English, social studies, math, and science in the analysis.

In this study, I integrate modern statistical methods and consider the moderating effects of demographic variables. I use both hierarchical linear modeling and machine learning algorithms such as gradient-boosted machines to investigate how modern techniques may improve predictive accuracy over traditional predictive methodologies.

This study addresses the following research questions:

1. Does increased course-taking in mathematics and science predict ACT performance when the model accounts for other academic and school characteristics?

2. Do student demographics (gender, race/ethnicity, and family income) moderate the relationship between course-taking and ACT performance?

3. Can modern machine learning models, such as gradient-boosted machines, improve the prediction of ACT performance over traditional regression methods?

Method

Analytical Sample

The analytical sample consisted of 453,439 students from the graduating class of 2023. These students took the ACT either as part of school-day testing or on a national test date. For each student, the ACT test used in this study was the most recent ACT test taken prior to graduation in the spring of 2023. The sample is further described in the descriptive statistics section below. This sample is a subset of all students who graduated in the class of 2023 and had valid ACT data (*N* = 608,830).

The study sample consisted of slightly more male than female students, mostly White students, and mostly students from families with incomes of greater than $100,000. There were slightly more students who had taken advanced coursework in English than had not, a similar number of students who had taken advanced coursework in math, science, and social studies, and mostly students who had taken English 9 through 11. About half of the students had taken mathematics coursework beyond Algebra II, most students had taken biology and chemistry, and most students had taken less than three years of social studies that did not include U.S. history, world history, American government, or another history class (Table 1). Although slight differences were seen in the percentages by demographics and achievement between the sample and the population, the sample and population were similar.

Table 1. Descriptive Statistics for the Population and Study Sample

Characteristic	Level	Population	Sample
N		608,830	453,439
Gender *n* (%)	Female	329,588 (54.1)	204,455 (45.1)
	Male	279,242 (45.9)	248,984 (54.9)
Race/ethnicity *n* (%)	African American	68,312 (11.2)	49,395 (10.9)
	American Indian/Alaska Native	4,768 (0.8)	—
	Hispanic	85,399 (14.0)	61,292 (13.5)
	Asian	31,063 (5.1)	23,130 (5.1)
	Native Hawaiian / Pacific Islander	1,083 (0.2)	—
	White	374,242 (61.5)	284,400 (62.7)
	Prefer not to respond / Missing	13,214 (2.2)	8,384 (1.8)
	Two or more / American Indian / Alaskan Native / Native Hawaiian / Pacific Islander	—	26,838 (5.9)
	Two or more races	30,749 (5.1)	—
Family income *n* (%)	<$36K	112,079 (18.4)	85,022 (18.8)
	$36K–$60K	91,246 (15.0)	70,825 (15.6)
	$60K–$100K	126,340 (20.8)	97,638 (21.5)
	>$100K	279,165 (45.9)	199,954 (44.1)
Advanced coursework in English *n* (%)	Not taken	278,855 (46.5)	205,499 (45.3)
	Taken	320,540 (53.5)	247,940 (54.7)
Advanced coursework in math *n* (%)	Not taken	304,579 (51.2)	227,611 (50.2)
	Taken	290,423 (48.8)	225,828 (49.8)
Advanced coursework in science *n* (%)	Not taken	293,379 (49.4)	220,122 (48.5)
	Taken	300,903 (50.6)	233,317 (51.5)
Advanced coursework in social studies *n* (%)	Not taken	297,538 (50.3)	225,979 (49.8)
	Taken	294,094 (49.7)	227,460 (50.2)
English courses taken *n* (%)	Less than Eng. 9–11	36,390 (6.0)	24,483 (5.4)
	Eng. 9–11	572,440 (94.0)	428,956 (94.6)
Math courses taken *n* (%)	Less than Algebra I, geometry, and Algebra II	46,177 (7.6)	32,249 (7.1)
	Algebra I, geometry, and Algebra II	228,864 (37.7)	171,150 (37.7)
	Beyond Algebra II	303,676 (50.0)	228,492 (50.4)
	Other math patterns	28,909 (4.8)	21,548 (4.8)
Science courses taken *n* (%)	Other less than 3 yr combinations	14,008 (2.3)	2,245 (0.5)
	General science	3,195 (0.5)	8,169 (1.8)
	Biology	92,750 (15.2)	73,744 (16.3)
	Biology and chemistry	296,954 (48.8)	227,410 (50.2)
	Biology, chemistry, and physics	179,576 (29.5)	124,706 (27.5)
	Other 3 yr combinations	22,347 (3.7)	17,165 (3.8)

Characteristic	Level	Population	Sample
Social studies courses taken *n* (%)	Other less than 3 yr combinations	257,936 (42.4)	185,497 (40.9)
	U.S. history, world history, and American government	65,490 (10.8)	52,040 (11.5)
	U.S. history, world history, American government, and other history	13,747 (2.3)	9,759 (2.2)
	Other 3 to 3.5 yr combinations	167,781 (27.6)	129,123 (28.5)
	Other 4+ yr combinations	103,876 (17.1)	77,020 (17.0)
HSGPA *M* (*SD*)		3.46 (0.57)	3.46 (0.58)
ACTC score *M* (*SD*)		21.24 (5.72)	21.17 (5.63)
% poverty at school *M* (*SD*)		14.90 (8.49)	14.57 (8.22)
Number of AP courses offered at school *M* (*SD*)		2.41 (1.56)	2.55 (1.50)
% of White students at school *M* (*SD*)		60.13 (26.76)	61.16 (26.11)

Note. In social studies, the courses do not follow a set sequence, and therefore, more courses does not necessarily mean more advanced courses as it may for math and science. “Other math patterns” in this study indicates unknown or unspecified math course-taking patterns. Other less-than-3-year combinations of science courses include cases where a student took less than 3 complete years of science coursework not captured by the other course patterns mentioned (for example, a student may have taken physical science, Earth science, and general science).

Measures

ACT Composite Score

Official ACT Composite (ACTC) scores were collected from the last ACT test that students took before graduating high school. These scores were gathered either during statewide school-day testing or during a national test administration.

Cumulative HSGPA

ACT averaged students’ self-reported grades in up to 23 courses across English, mathematics, social studies, and natural science to determine each student’s HSGPA. Sanchez and Buddin (2016) showed a strong correlation between students’ self-reported HSGPA and their transcript GPA. Additional research (Camara et al., 2003; Kuncel et al., 2005; Shaw & Mattern, 2009) supports the reliability of self-reported data for research purposes.

Demographic Variables

The study investigated three demographic variables: gender, race/ethnicity, and family income, as shown in Table 1. Students self-reported their gender as male, female, another gender, or prefer not to respond; some did not respond at all. For this analysis, students who identified as another gender, preferred not to respond, or did not provide a response were excluded. This exclusion was done to aid in the interpretability of the results because of the very low number of students in these categories.

Students could identify their racial/ethnic background as Asian, Black, Hispanic, American Indian / Alaska Native, Native Hawaiian / Pacific Islander, White, two or more races, or prefer not to respond; some did not respond. Due to the small number of students in some groups, I combined data for those identifying as American Indian / Alaska Native (0.8%), Native Hawaiian / Pacific Islander (0.2%), and two or more races (5.1%).

Family income was categorized into four groups: below \$36,000, \$36,000–\$60,000, \$60,000–\$100,000, and above \$100,000. Students with missing family income data were omitted.

Coursework Taken

Students reported information related to their high school coursework. From this information, I determined whether students had taken advanced coursework in English, math, natural science, or social studies. In this study, advanced coursework included honors, AP, and IB courses. Additionally, I examined course-taking patterns in English, math, science, and social studies. As an example, for math, course-taking patterns included less than Algebra I, geometry, and Algebra II; Algebra I, geometry, and Algebra II; beyond Algebra II; and other math patterns (see Table 1 for full course listings).

High School Characteristics

The following school characteristics were included in the study: percentage of students at a school who met poverty guidelines, number of AP courses offered at a school, and the percentage of White students at a school.

Data Analysis

I estimated six models to predict ACTC scores using various combinations of HSGPA; course-taking patterns in math, social studies, and science; indicators for advanced course-taking in English, social studies, math, and science; high school coursework taken; and school-level characteristics like the percentage of students at a school meeting federal poverty guidelines, the number of AP courses offered at a school, and the percentage of White students at a school. Note that course-taking in English is not used in the models because of the lack of variability (i.e., almost all the students took English 9–11). All continuous predictors such as ACTC score and HSGPA were standardized to have a mean of 0 and a standard deviation of 1.

Model 1 is a hierarchical linear model (HLM) that accounts for student nesting within postsecondary institutions. This model includes all predictors without any interactions, providing a comprehensive analysis of the main effects between high school coursework and ACTC score. The predictors in Model 1 include high school GPA; indicators for advanced coursework in English, social studies, math, and science; and school-level characteristics such as the percentage of students at a school meeting federal poverty guidelines, the number of AP courses offered at a school, and the percentage of White students at a school.

Model 1. $ACTC = HSGPA + Advanced\ Courses\ in\ English + Advanced\ Courses\ in\ Social\ Studies + Advanced\ Courses\ in\ Math + Advanced\ Courses\ in\ Science + Social\ Studies\ Course\ Taking\ Pattern + Math\ Course\ Taking\ Pattern + Science\ Course\ Taking\ Pattern + \%\ Meeting\ Poverty\ Guidelines\ at\ School + Number\ of\ AP\ Courses\ Offered\ at\ School + \%\ of\ students\ at\ School\ of\ White\ race/ethnicity$

Model 2 builds upon Model 1 by incorporating an interaction between course-taking and gender. While Model 1 includes all predictors without any interactions, Model 2 provides a more nuanced analysis by examining how the relationship between high school coursework and gender varies.

Model 2. $ACTC = HSGPA + Advanced\ Courses\ in\ English + Advanced\ Courses\ in\ Social\ Studies + Advanced\ Courses\ in\ Math + Advanced\ Courses\ in\ Science + ((Social\ Studies\ Course\ Taking\ Pattern + Math\ Course\ Taking\ Pattern + Science\ Course\ Taking\ Pattern) * Gender) + \%\ Meeting\ Poverty\ Guidelines\ at\ School + Number\ of\ AP\ Courses\ Offered\ at\ School + \%\ of\ students\ at\ School\ of\ White\ race/ethnicity$

Model 3 builds upon Model 1 by incorporating an interaction between course-taking and race/ethnicity.

Model 3. $ACTC = HSGPA + Advanced\ Courses\ in\ English + Advanced\ Courses\ in\ Social\ Studies + Advanced\ Courses\ in\ Math + Advanced\ Courses\ in\ Science + ((Social\ Studies\ Course\ Taking\ Pattern + Math\ Course\ Taking\ Pattern + Science\ Course\ Taking\ Pattern) * Race/ethnicity) + \%\ Meeting\ Poverty\ Guidelines\ at\ School + Number\ of\ AP\ Courses\ Offered\ at\ School + \%\ of\ students\ at\ School\ of\ White\ race/ethnicity$

Model 4 builds upon Model 1 by incorporating an interaction between course-taking and family income.

Model 4. $ACTC = HSGPA + Advanced\ Courses\ in\ English + Advanced\ Courses\ in\ Social\ Studies + Advanced\ Courses\ in\ Math + Advanced\ Courses\ in\ Science + ((Social\ Studies\ Course\ Taking\ Pattern + Math\ Course\ Taking\ Pattern + Science\ Course\ Taking\ Pattern) * Family\ Income) + \%\ Meeting\ Poverty\ Guidelines\ at\ School + Number\ of\ AP\ Courses\ Offered\ at\ School + \%\ of\ students\ at\ School\ of\ White\ race/ethnicity$

Model 5 is a GBM model that mirrors Model 1 in that it does not include demographic information.

Model 5. $GBM1: ACTC = HSGPA + Advanced\ Courses\ in\ English + Advanced\ Courses\ in\ Social\ Studies + Advanced\ Courses\ in\ Math + Advanced\ Courses\ in\ Science + Social\ Studies\ Course\ Taking\ Pattern + Math\ Course\ Taking\ Pattern + Science\ Course\ Taking\ Pattern + \%\ Meeting\ Poverty\ Guidelines\ at\ School + Number\ of\ AP\ Courses\ Offered\ at\ School + \%\ of\ students\ at\ School\ of\ White\ race/ethnicity$

Model 6 is a GBM model that includes all predictors, including all three demographic characteristics. GBM models inherently account for interactions in the model-building process, so those interactions are not explicitly specified.

Model 6. $GBM2: ACTC = HSGPA + Advanced\ Courses\ in\ English + Advanced\ Courses\ in\ Social\ Studies + Advanced\ Courses\ in\ Math + Advanced\ Courses\ in\ Science + Social\ Studies\ Course\ Taking\ Pattern + Math\ Course\ Taking\ Pattern + Science\ Course\ Taking\ Pattern + Gender + Race/ethnicity + Family\ Income + \%\ Meeting\ Poverty\ Guidelines\ at\ School + Number\ of\ AP\ Courses\ Offered\ at\ School + \%\ of\ students\ at\ School\ of\ White\ race/ethnicity$

In both GBM models, Model 5 and Model 6, I used a grid of hyperparameters to identify the optimal number of trees for the model, interaction depth, shrinkage parameter, and minimum number of observations to use in a node. For both of these GBM models, I explored 500, 1,000, and 1,500 trees. Three interaction depths were explored: three, five, and seven. It is worth noting that up to three-, five-, or seven-way interactions could occur between any predictors in the model. Three shrinkage parameters were explored: 0.01, 0.05, and 0.1. Finally, two values for the minimum number of observations required for nodes were explored: 10 and 20.

Given the complexity of incorporating all possible interactions in a single HLM (as is done with GBM Model 6), I elected to run simpler HLMs with only one demographic interaction at a time. This means we can compare Models 1 and 5 which have no demographics, and Models 2–4 with Model 6, all of which have demographics.[1]

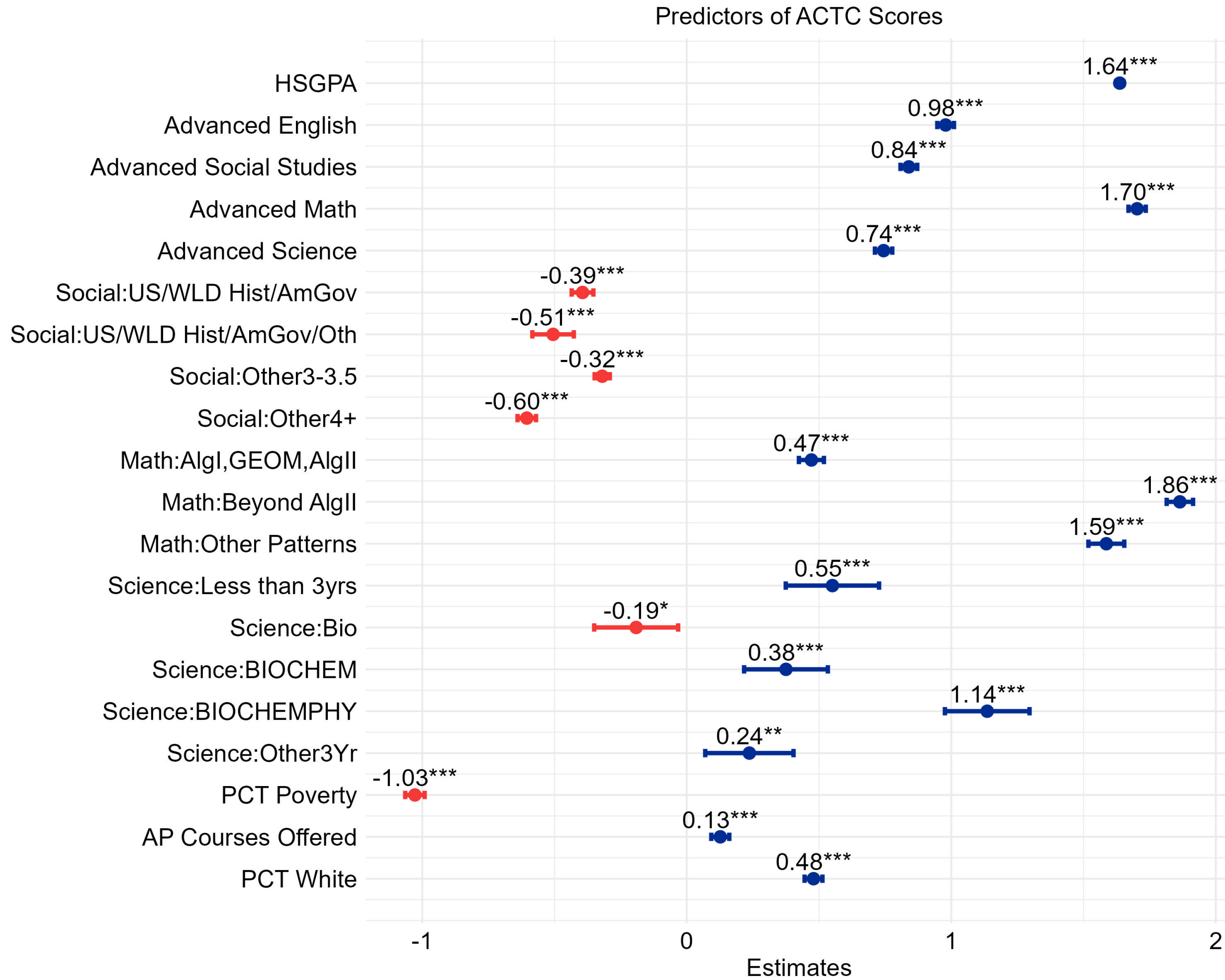
Results

Hierarchical Linear Model Results

Figure 1 displays the standardized coefficients for Model 1, which includes all predictors without any interactions. All predictors in the model were statistically significant ($p < .001$). Table 2 displays the estimated ACTC scores by coursework. Generally speaking, for math and science coursework, we see a slight increase in estimated ACTC score as course rigor increases. There is no clear pattern of increase or decrease with social studies courses, as they do not follow a sequence of more advanced courses. See Table A1 for model results.

[1] I revisit the possibility of a HLM with all demographic interactions later in the paper. The complexity of that model makes it difficult to interpret and use in a practical manner.

Figure 1. Plot of Model 1 Standardized Coefficients



Note. The reference groups are not taking advanced English, social studies, math, or science; other less-than-3-year combinations of social studies courses; less than Algebra I, geometry, and Algebra II; and general science.

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

Table 2. Estimated Marginal Means for Coursework Taken for Model 1

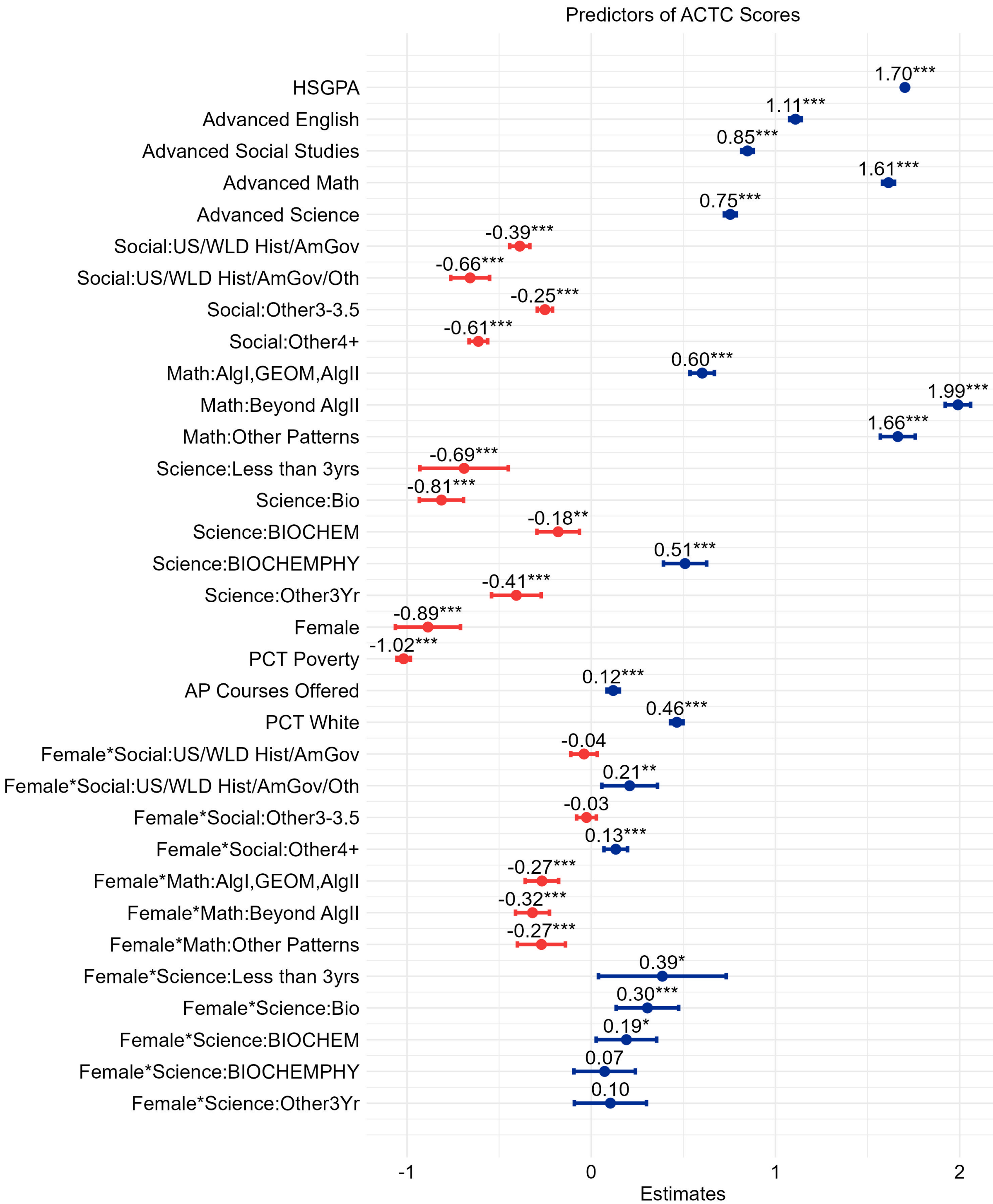
Subject	Coursework	Marginal mean	*SE*	Lower 95% CI	Upper 95% CI
Math	Less than Algebra I, geometry, and Algebra II	19.64	0.03	19.58	19.71
	Algebra I, geometry, and Algebra II	20.12	0.03	20.06	20.17
	Beyond Algebra II	21.51	0.03	21.46	21.56
	Other math patterns	21.23	0.04	21.16	21.30
Science[2]	General science	20.27	0.08	20.11	20.43
	Other less than 3 yr combinations	20.82	0.05	20.73	20.91
	Biology	20.08	0.02	20.03	20.13
	Biology and chemistry	20.65	0.02	20.61	20.69
	Biology, chemistry, and physics	21.41	0.02	21.36	21.45
	Other 3 yr combinations	20.51	0.04	20.44	20.58
Social studies	Other less than 3 yr combinations	20.99	0.02	20.94	21.04
	U.S. hist., world hist., and Am. gov.	20.59	0.03	20.54	20.65
	U.S. hist., world hist., Am. gov., and other history	20.48	0.05	20.39	20.57
	Other 3 to 3.5 yr combinations	20.67	0.03	20.62	20.72
	Other 4+ yr combinations	20.38	0.03	20.33	20.44

Note. "Less than Algebra I, geometry, and Algebra II" indicates that a student took fewer courses than Algebra I, geometry, and Algebra II.

Figure 2 presents the regression estimates from Model 2, which incorporates an interaction between course-taking and gender. Table 3 displays the estimated ACTC scores by coursework taken and gender. See Table A2 for model results. The results show that gender is a significant moderator of the effect of coursework on ACTC scores. Overall, the gender interaction effects indicate that male students tend to have higher ACTC scores across various coursework categories compared to female students.

[2] There is an apparent discrepancy between some coefficients in Figure 1 and the marginal means in Table 2. The discrepancy arises because Figure 1 displays standardized coefficients, which show the independent effect of each course on ACTC scores after the model accounts for other factors. In contrast, Table 2 presents marginal means, which are group-level averages, without adjusting for confounders. For instance, biology may have a negative coefficient in Figure 1, indicating that, when the model controls for other factors, it predicts lower ACTC scores compared to general science. However, biology's higher marginal mean in Table 2 suggests that students taking this course generally score higher, but this advantage diminishes when we adjust for other predictors in the regression model.

Figure 2. Plot of Model 2 Standardized Coefficients Including an Interaction With Gender



Note. The reference groups are not taking advanced English, social studies, math, or science; other less-than-3-year combinations of social studies courses; less than Algebra I, geometry, and Algebra II; and general science.

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

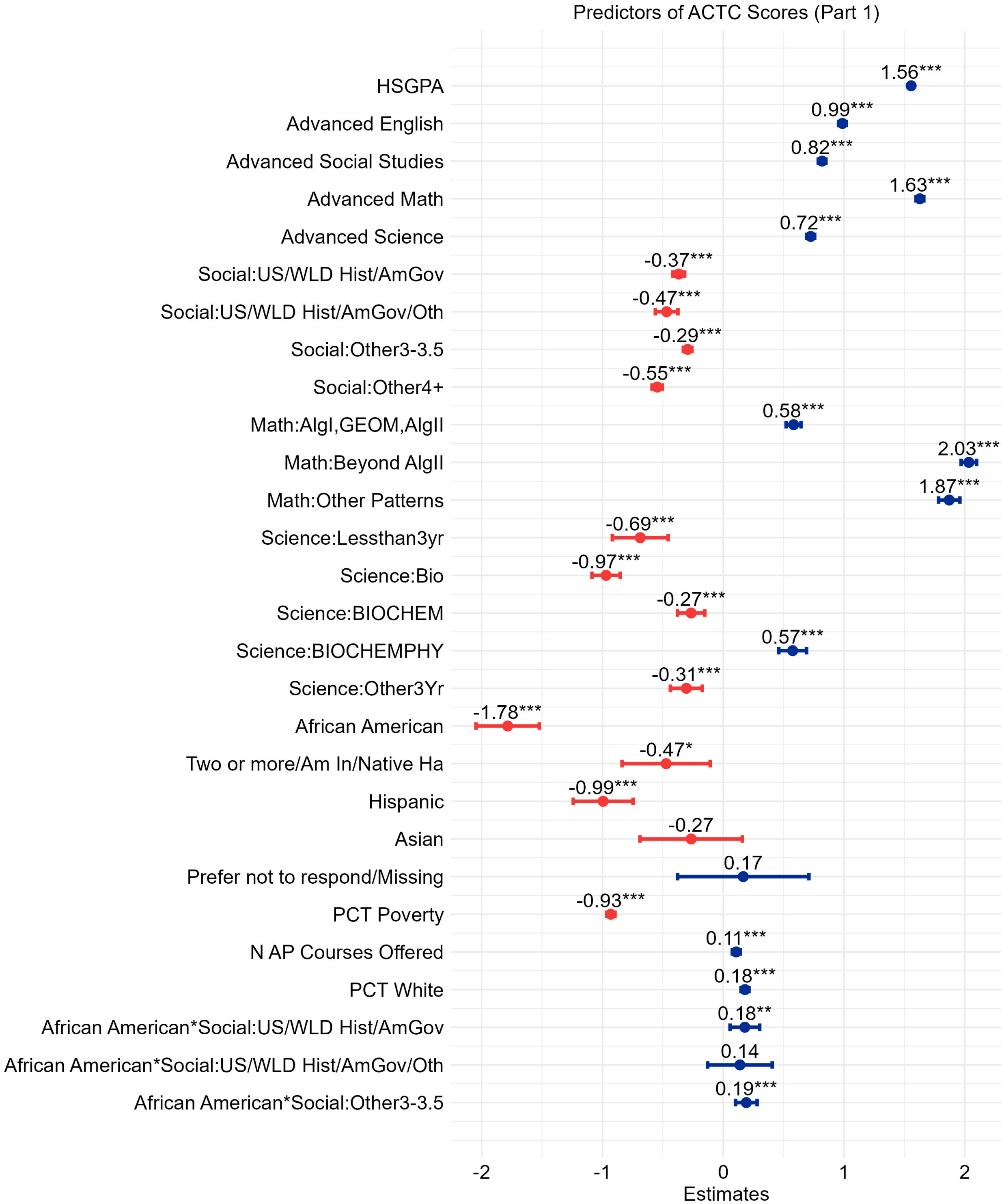
Table 3. Estimated Marginal Means for Coursework Taken for Model 2 by Gender

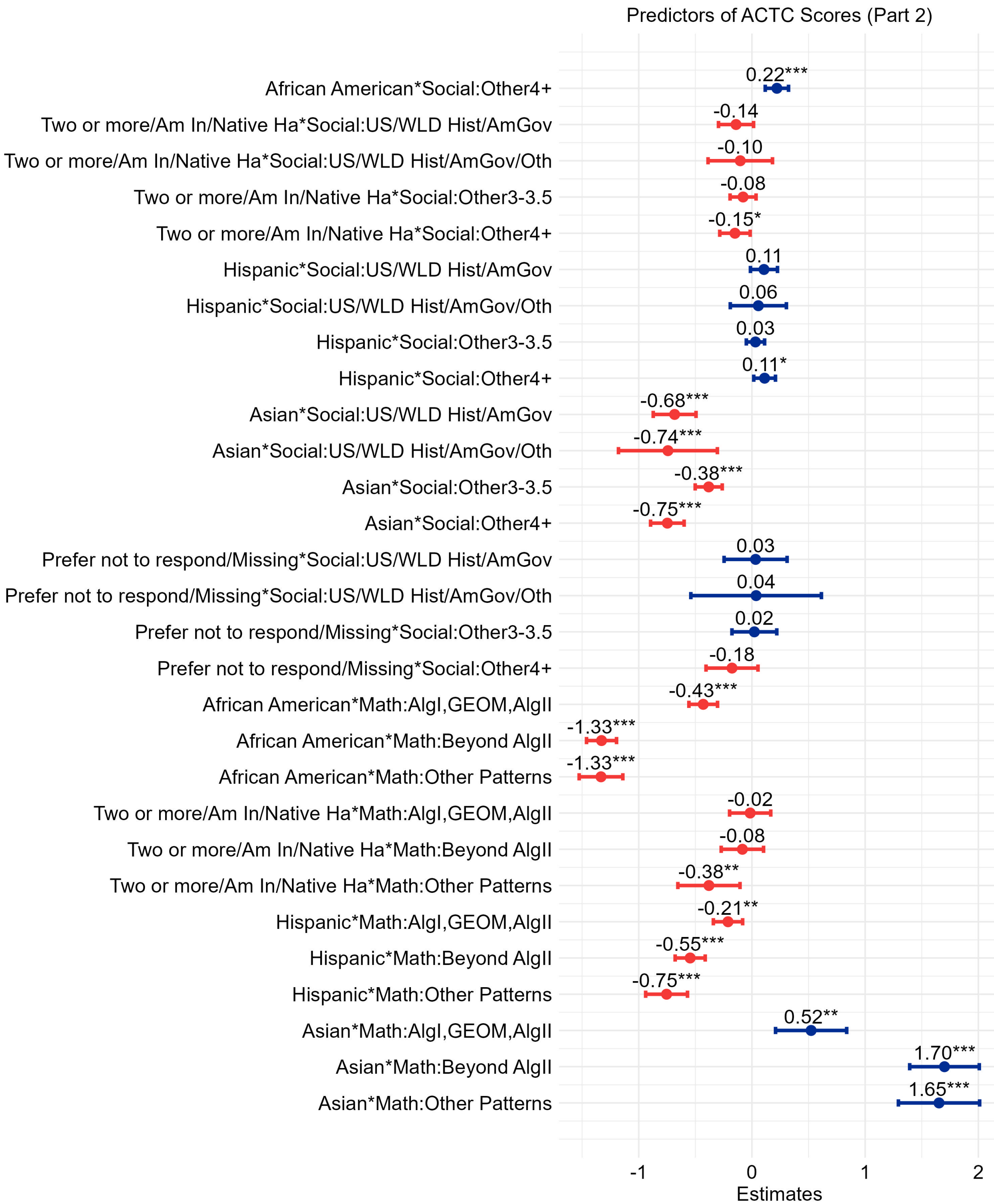
Interaction	Gender	Coursework	Marginal mean	*SE*	Lower 95% CI	Upper 95% CI
Math * Gender	Male	Less than Algebra I, geometry, and Algebra II	20.00	0.04	19.92	20.08
	Female	Less than Algebra I, geometry, and Algebra II	19.35	0.04	19.26	19.43
	Male	Algebra I, geometry, and Algebra II	20.60	0.03	20.54	20.66
	Female	Algebra I, geometry, and Algebra II	19.68	0.03	19.62	19.74
	Male	Beyond Algebra II	21.99	0.03	21.93	22.05
	Female	Beyond Algebra II	21.02	0.03	20.95	21.08
	Male	Other math patterns	21.66	0.05	21.57	21.75
	Female	Other math patterns	20.74	0.05	20.65	20.83
Science *	Male	General science	20.64	0.11	20.42	20.85
	Female	General science	19.98	0.12	19.75	20.21
	Male	Other less than 3 yr combinations	21.33	0.06	21.21	21.45
	Female	Other less than 3 yr combinations	20.28	0.06	20.16	20.41
	Male	Biology	20.51	0.03	20.46	20.57
	Female	Biology	19.77	0.03	19.72	19.83
	Male	Biology and chemistry	21.15	0.03	21.10	21.20
	Female	Biology and chemistry	20.29	0.03	20.24	20.34
	Male	Biology, chemistry, and physics	21.84	0.03	21.78	21.89
	Female	Biology, chemistry, and physics	20.86	0.03	20.81	20.92
	Male	Other 3 yr combinations	20.92	0.04	20.83	21.01
	Female	Other 3 yr combinations	19.98	0.05	19.89	20.07
Social studies * Gender	Male	Other less than 3 yr combinations	21.45	0.03	21.39	21.50
	Female	Other less than 3 yr combinations	20.52	0.03	20.46	20.58
	Male	U.S. hist., world hist., and Am. gov.	21.06	0.04	20.99	21.13
	Female	U.S. hist., world hist., and Am. gov.	20.09	0.04	20.02	20.17
	Male	U.S. hist., world hist., Am. gov., and other history	20.79	0.06	20.67	20.90
	Female	U.S. hist., world hist., Am. gov., and other history	20.07	0.06	19.95	20.20
	Male	Other 3 to 3.5 yr combinations	21.19	0.03	21.13	21.26
	Female	Other 3 to 3.5 yr combinations	20.24	0.03	20.18	20.31
	Male	Other 4+ yr combinations	20.83	0.04	20.76	20.90
	Female	Other 4+ yr combinations	20.04	0.03	19.97	20.11

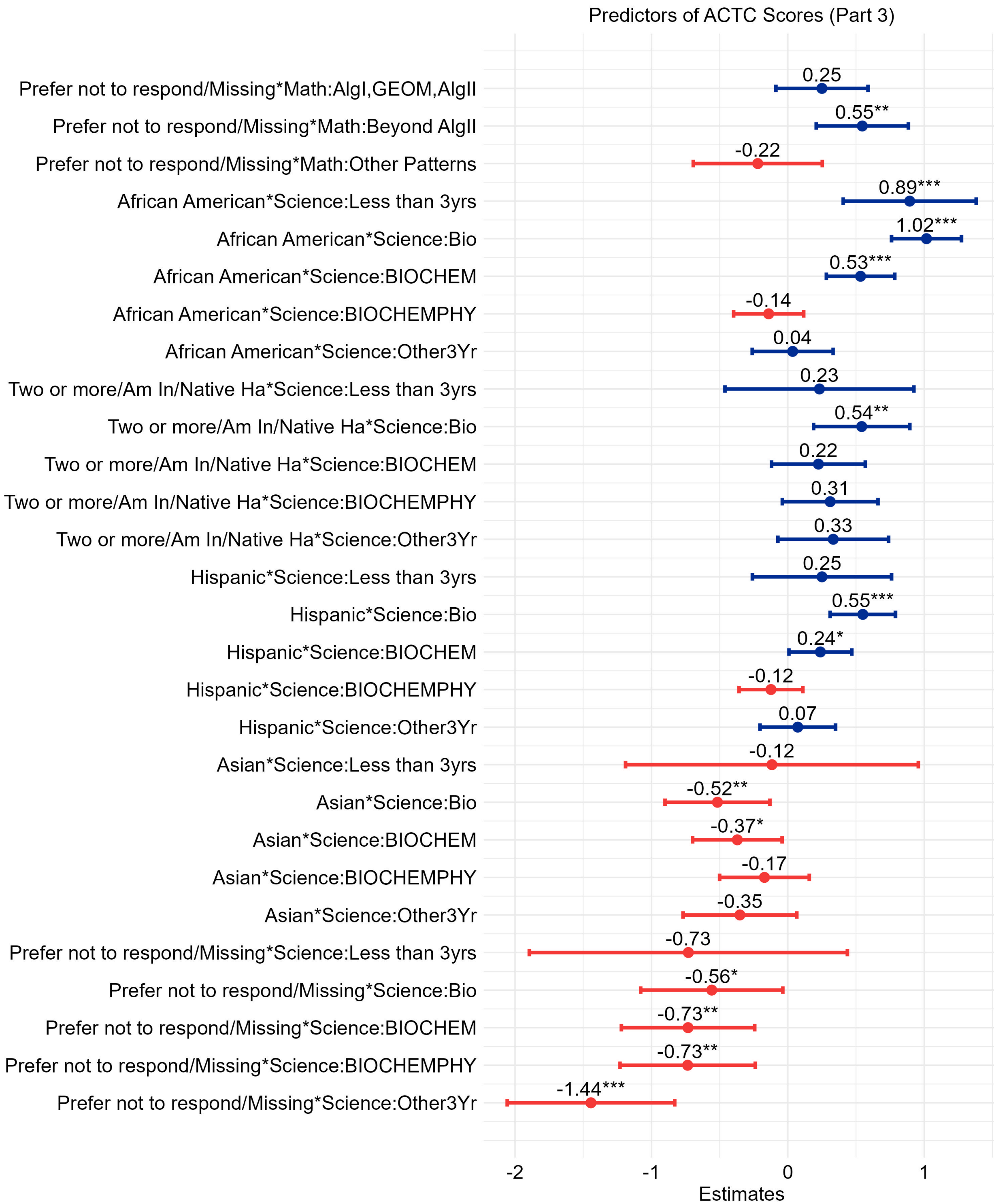
Note. “Less than Algebra I, geometry, and Algebra II” indicates that a student took fewer courses than Algebra I, geometry, and Algebra II.

Figure 3 presents the regression estimates from Model 3, which incorporates an interaction between course-taking and race/ethnicity. All predictors in the model were statistically significant ($p < .001$). Table 4 displays the estimated ACTC scores by coursework taken and race/ethnicity. We can see that, in general, race/ethnicity significantly moderates the relationship between high school coursework and ACTC scores. As an example, White students consistently scored higher than African American, Hispanic, and other racial/ethnic groups across all math course-taking patterns. A similar relationship was found for science courses, where White students who took biology, chemistry, and physics scored higher (21.85) than African American students (19.30). This pattern also holds for other science categories like general science and biology. For social studies, a similar pattern emerged: White students outperformed other racial/ethnic groups across the coursework patterns examined. See Table A3 for model results.

Figure 3. Plot of Model 3 Standardized Coefficients Including an Interaction With Race/Ethnicity




Predictors of ACTC Scores (Part 2)
African American*Social:Other4+
Two or more/Am In/Native Ha*Social:US/WLD Hist/AmGov
Two or more/Am In/Native Ha*Social:US/WLD Hist/AmGov/Oth
Two or more/Am In/Native Ha*Social:Other3-3.5
Two or more/Am In/Native Ha*Social:Other4+
Hispanic*Social:US/WLD Hist/AmGov
Hispanic*Social:US/WLD Hist/AmGov/Oth
Hispanic*Social:Other3-3.5
Hispanic*Social:Other4+
Asian*Social:US/WLD Hist/AmGov
Asian*Social:US/WLD Hist/AmGov/Oth
Asian*Social:Other3-3.5
Asian*Social:Other4+
Prefer not to respond/Missing*Social:US/WLD Hist/AmGov
Prefer not to respond/Missing*Social:US/WLD Hist/AmGov/Oth
Prefer not to respond/Missing*Social:Other3-3.5
Prefer not to respond/Missing*Social:Other4+
African American*Math:AlgI,GEOM,AlgII
African American*Math:Beyond AlgII
African American*Math:Other Patterns
Two or more/Am In/Native Ha*Math:AlgI,GEOM,AlgII
Two or more/Am In/Native Ha*Math:Beyond AlgII
Two or more/Am In/Native Ha*Math:Other Patterns
Hispanic*Math:AlgI,GEOM,AlgII
Hispanic*Math:Beyond AlgII
Hispanic*Math:Other Patterns
Asian*Math:AlgI,GEOM,AlgII
Asian*Math:Beyond AlgII
Asian*Math:Other Patterns
0.22***
-0.14
-0.10
-0.08
-0.15*
0.11
0.06
0.03
0.11*
-0.68***
-0.74***
-0.38***
-0.75***
0.03
0.04
0.02
-0.18
-0.43***
-1.33***
-1.33***
-0.02
-0.08
-0.38**
-0.21**
-0.55***
-0.75***
0.52**
1.70***
1.65***
-1
0
1
2
Estimates



Note. The reference groups are not taking advanced English, social studies, math, or science; other less-than-3-year combinations of social studies courses; less than Algebra I, geometry, and Algebra II; and general science.

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

Table 4. Estimated Marginal Means for Coursework Taken for Model 3 by Race/Ethnicity

Subject	Race/ethnicity	Coursework	Marginal mean	*SE*	Lower 95% CI	Upper 95% CI
Math	White	Less than Algebra I, geom., and Algebra II	19.88	0.04	19.80	19.95
	African American	Less than Algebra I, geom., and Algebra II	18.63	0.07	18.49	18.76
	Two or more / American Indian / Native Hawaiian	Less than Algebra I, geom., and Algebra II	19.58	0.10	19.39	19.78
	Hispanic	Less than Algebra I, geom., and Algebra II	19.11	0.07	18.97	19.24
	Asian	Less than Algebra I, geom., and Algebra II	18.85	0.17	18.50	19.19
	Prefer not to respond / Missing	Less than Algebra I, geom., and Algebra II	19.33	0.18	18.97	19.68
	White	Algebra I, geom., and Algebra II	20.46	0.03	20.40	20.52
	African American	Algebra I, geom., and Algebra II	18.78	0.06	18.67	18.89
	Two or more / American Indian / Native Hawaiian	Algebra I, geom., and Algebra II	20.15	0.07	20.01	20.29
	Hispanic	Algebra I, geom., and Algebra II	19.48	0.05	19.37	19.59
	Asian	Algebra I, geom., and Algebra II	19.95	0.12	19.72	20.18
	Prefer not to respond / Missing	Algebra I, geom., and Algebra II	20.16	0.13	19.89	20.42
	White	Beyond Algebra II	21.91	0.03	21.85	21.97
	African American	Beyond Algebra II	19.33	0.06	19.22	19.44
	Two or more / American Indian / Native Hawaiian	Beyond Algebra II	21.53	0.07	21.39	21.67
	Hispanic	Beyond Algebra II	20.60	0.05	20.49	20.70
	Asian	Beyond Algebra II	22.58	0.11	22.37	22.79
	Prefer not to respond / Missing	Beyond Algebra II	21.90	0.13	21.65	22.16
	White	Other math patterns	21.75	0.04	21.66	21.83
	African American	Other math patterns	19.16	0.09	19.00	19.33
	Two or more / American Indian / Native Hawaiian	Other math patterns	21.07	0.12	20.83	21.31
	Hispanic	Other math patterns	20.22	0.08	20.07	20.38
	Asian	Other math patterns	22.37	0.14	22.09	22.64
	Prefer not to respond / Missing	Other math patterns	20.98	0.21	20.56	21.39
Science	White	General science	20.59	0.11	20.38	20.79
	African American	General science	19.07	0.19	18.69	19.45
	Two or more / American Indian / Native Hawaiian	General science	20.13	0.29	19.56	20.71

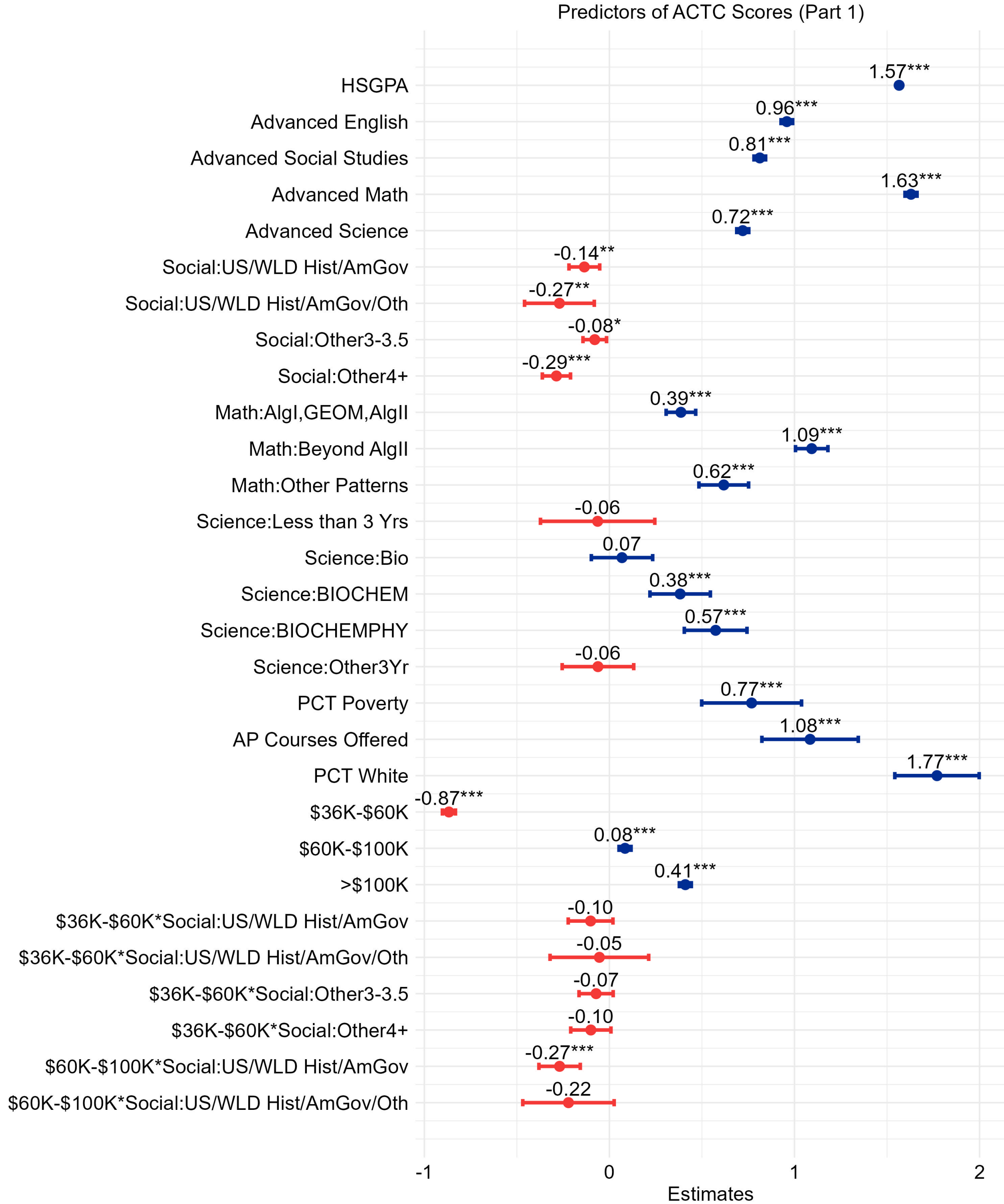
Subject	Race/ethnicity	Coursework	Marginal mean	*SE*	Lower 95% CI	Upper 95% CI
	Hispanic	General science	19.53	0.21	19.11	19.94
	Asian	General science	20.66	0.52	19.65	21.67
	Prefer not to respond / Missing	General science	20.15	0.54	19.09	21.21
	White	Other less than 3 yr combinations	21.27	0.06	21.16	21.39
	African American	Other less than 3 yr combinations	18.86	0.12	18.63	19.09
	Two or more / American Indian / Native Hawaiian	Other less than 3 yr combinations	20.59	0.17	20.26	20.91
	Hispanic	Other less than 3 yr combinations	19.96	0.10	19.76	20.17
	Asian	Other less than 3 yr combinations	21.47	0.16	21.15	21.79
	Prefer not to respond / Missing	Other less than 3 yr combinations	21.57	0.25	21.08	22.05
	White	Biology	20.30	0.03	20.25	20.36
	African American	Biology	18.91	0.05	18.81	19.01
	Two or more / American Indian / Native Hawaiian	Biology	20.16	0.06	20.03	20.28
	Hispanic	Biology	19.54	0.05	19.44	19.64
	Asian	Biology	19.98	0.12	19.75	20.21
	Prefer not to respond / Missing	Biology	20.04	0.13	19.79	20.29
	White	Biology and chemistry	21.01	0.02	20.96	21.05
	African American	Biology and chemistry	19.13	0.04	19.04	19.21
	Two or more / American Indian / Native Hawaiian	Biology and chemistry	20.54	0.05	20.44	20.65
	Hispanic	Biology and chemistry	19.94	0.04	19.86	20.02
	Asian	Biology and chemistry	20.83	0.07	20.69	20.97
	Prefer not to respond / Missing	Biology and chemistry	20.57	0.10	20.37	20.76
	White	Biology, chemistry, and physics	21.85	0.03	21.80	21.90
	African American	Biology, chemistry, and physics	19.30	0.05	19.20	19.39
	Two or more / American Indian / Native Hawaiian	Biology, chemistry, and physics	21.47	0.06	21.35	21.59
	Hispanic	Biology, chemistry, and physics	20.41	0.04	20.33	20.50
	Asian	Biology, chemistry, and physics	21.87	0.07	21.72	22.01
	Prefer not to respond / Missing	Biology, chemistry, and physics	21.41	0.11	21.20	21.61
	White	Other 3 yr combinations	20.97	0.04	20.88	21.05
	African American	Other 3 yr combinations	18.59	0.09	18.42	18.76

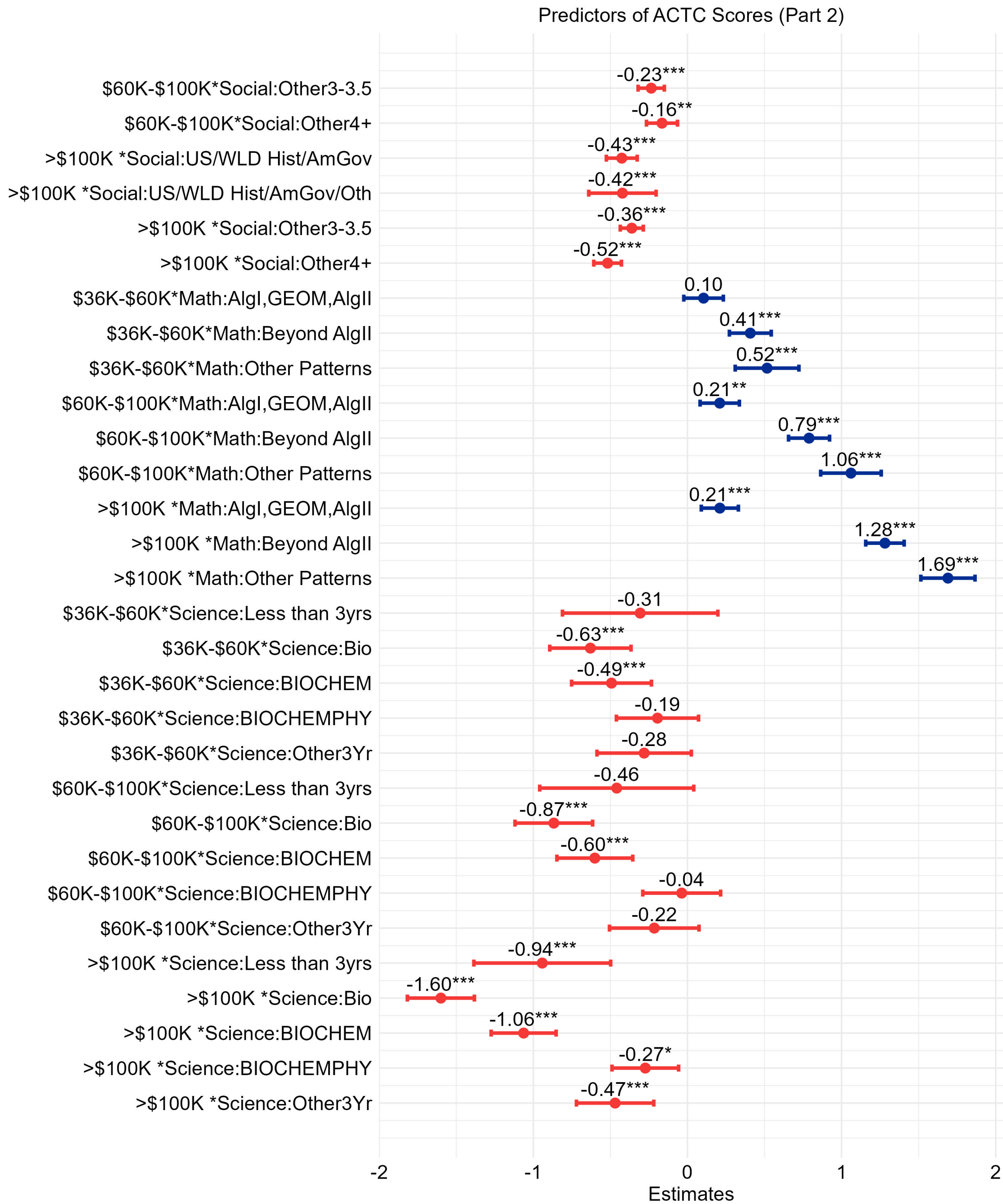
Subject	Race/ethnicity	Coursework	Marginal mean	*SE*	Lower 95% CI	Upper 95% CI
	Two or more / American Indian / Native Hawaiian	Other 3 yr combinations	20.61	0.12	20.38	20.84
	Hispanic	Other 3 yr combinations	19.73	0.08	19.57	19.89
	Asian	Other 3 yr combinations	20.81	0.15	20.52	21.09
	Prefer not to respond / Missing	Other 3 yr combinations	19.82	0.21	19.41	20.23
	White	Other less than 3 yr combinations	21.33	0.03	21.28	21.39
	African American	Other less than 3 yr combinations	19.17	0.05	19.07	19.26
	Two or more / American Indian / Native Hawaiian	Other less than 3 yr combinations	21.01	0.07	20.88	21.15
	Hispanic	Other less than 3 yr combinations	20.13	0.05	20.03	20.22
	Asian	Other less than 3 yr combinations	21.78	0.10	21.58	21.98
	Prefer not to respond / Missing	Other less than 3 yr combinations	20.94	0.12	20.71	21.18
	White	U.S. hist., world hist., and Am. gov.	20.96	0.03	20.90	21.03
	African American	U.S. hist., world hist., and Am. gov.	18.98	0.07	18.84	19.11
	Two or more / American Indian / Native Hawaiian	U.S. hist., world hist., and Am. gov.	20.51	0.09	20.33	20.69
	Hispanic	U.S. hist., world hist., and Am. gov.	19.86	0.07	19.73	20.00
Social studies	Asian	U.S. hist., world hist., and Am. gov.	20.73	0.13	20.48	20.99
	Prefer not to respond / Missing	U.S. hist., world hist., and Am. gov.	20.61	0.17	20.28	20.93
	White	U.S. hist., world hist., Am. gov., and other history	20.86	0.05	20.76	20.97
	African American	U.S. hist., world hist., Am. gov., and other history	18.84	0.13	18.58	19.09
	Two or more / American Indian / Native Hawaiian	U.S. hist., world hist., Am. gov., and other history	20.44	0.15	20.15	20.73
	Hispanic	U.S. hist., world hist., Am. gov., and other history	19.71	0.12	19.47	19.96
	Asian	U.S. hist., world hist., Am. gov., and other history	20.57	0.24	20.11	21.04
	Prefer not to respond / Missing	U.S. hist., world hist., Am. gov., and other history	20.51	0.30	19.92	21.11
	White	Other 3 to 3.5 yr combinations	21.04	0.03	20.98	21.10

Subject	Race/ethnicity	Coursework	Marginal mean	*SE*	Lower 95% CI	Upper 95% CI
	African American	Other 3 to 3.5 yr combinations	19.06	0.05	18.95	19.17
	Two or more / American Indian / Native Hawaiian	Other 3 to 3.5 yr combinations	20.64	0.08	20.49	20.79
	Hispanic	Other 3 to 3.5 yr combinations	19.86	0.05	19.76	19.97
	Asian	Other 3 to 3.5 yr combinations	21.11	0.11	20.89	21.32
	Prefer not to respond / Missing	Other 3 to 3.5 yr combinations	20.67	0.13	20.41	20.93
	White	Other 4+ yr combinations	20.79	0.03	20.72	20.85
	African American	Other 4+ yr combinations	18.84	0.06	18.72	18.96
	Two or more / American Indian / Native Hawaiian	Other 4+ yr combinations	20.32	0.08	20.15	20.48
	Hispanic	Other 4+ yr combinations	19.69	0.06	19.58	19.81
	Asian	Other 4+ yr combinations	20.49	0.12	20.26	20.72
	Prefer not to respond / Missing	Other 4+ yr combinations	20.22	0.15	19.93	20.51

Figure 4 presents the coefficients for Model 4. Table 5 provides the estimated ACTC scores by coursework taken and family income. The interaction coefficients in Figure 4 demonstrate that family income significantly moderates the relationship between high school coursework and ACTC scores. For example, when we look at math courses, we see that students from higher-income families consistently scored higher than students from lower-income families across all math course-taking patterns. One such example is for students from families with an income above $100,000 who took courses beyond Algebra II versus students from families with an income below $36,000 with the same course-taking pattern. The former group had an estimated ACTC score of 22.14, while the latter had a score of 20.16. For science, a similar income differential was observed. For example, students from higher-income families who took biology, chemistry, and physics scored higher (21.96) than students from lower-income families (20.01). The same relationship was observed for social studies. As an example, students from families with an income above $100,000 who took U.S. history, world history, American government, and other history courses had an ACT score of 20.89, while students from families with an income below $36,000 had a score of 19.47. See Table A4 for model results.

Figure 4. Plot of Model 4 Standardized Coefficients Including an Interaction With Family Income





Note. The reference groups are not taking advanced English, social studies, math, or science; other less-than-3-year combinations of social studies courses; less than Algebra I, geometry, and Algebra II; and general science.

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

Table 5. Estimated Marginal Means for Coursework Taken for Model 4 by Family Income

Subject	Family income	Coursework	Marginal mean	*SE*	Lower 95% CI	Upper 95% CI
Math	<$36K	Less than Algebra I, geom., and Algebra II	19.07	0.05	18.97	19.16
	$36K–$60K	Less than Algebra I, geom., and Algebra II	19.45	0.06	19.33	19.57
	$60K–$100K	Less than Algebra I, geom., and Algebra II	19.61	0.06	19.49	19.73
	>$100K	Less than Algebra I, geom., and Algebra II	19.77	0.05	19.66	19.87
	<$36K	Algebra I, geom., and Algebra II	19.45	0.04	19.37	19.53
	$36K–$60K	Algebra I, geom., and Algebra II	19.94	0.05	19.85	20.04
	$60K–$100K	Algebra I, geom., and Algebra II	20.20	0.05	20.12	20.29
	>$100K	Algebra I, geom., and Algebra II	20.36	0.04	20.29	20.44
	<$36K	Beyond Algebra II	20.16	0.04	20.07	20.24
	$36K–$60K	Beyond Algebra II	20.95	0.05	20.86	21.05
	$60K–$100K	Beyond Algebra II	21.49	0.04	21.40	21.58
	>$100K	Beyond Algebra II	22.14	0.04	22.07	22.21
	<$36K	Other math patterns	19.68	0.07	19.55	19.82
	$36K–$60K	Other math patterns	20.59	0.08	20.43	20.74
	$60K–$100K	Other math patterns	21.29	0.07	21.15	21.42
	>$100K	Other math patterns	22.07	0.05	21.97	22.17
Science	<$36K	General science	19.38	0.14	19.10	19.65
	$36K–$60K	General science	20.03	0.18	19.68	20.38
	$60K–$100K	General science	20.34	0.18	19.99	20.69
	>$100K	General science	20.65	0.15	20.36	20.95
	<$36K	Other less than 3 yr combinations	19.44	0.09	19.27	19.61
	$36K–$60K	Other less than 3 yr combinations	20.40	0.10	20.19	20.61
	$60K–$100K	Other less than 3 yr combinations	20.86	0.10	20.67	21.05
	>$100K	Other less than 3 yr combinations	21.66	0.07	21.52	21.80
	<$36K	Biology	19.51	0.04	19.43	19.58
	$36K–$60K	Biology	19.84	0.04	19.76	19.92
	$60K–$100K	Biology	20.06	0.04	19.99	20.14
	>$100K	Biology	20.13	0.03	20.06	20.20
	<$36K	Biology and chemistry	19.82	0.03	19.75	19.89
	$36K–$60K	Biology and chemistry	20.29	0.04	20.22	20.36
	$60K–$100K	Biology and chemistry	20.64	0.03	20.58	20.71
	>$100K	Biology and chemistry	20.98	0.03	20.93	21.03
	<$36K	Biology, chemistry, and physics	20.01	0.04	19.93	20.09

Subject	Family income	Coursework	Marginal mean	*SE*	Lower 95% CI	Upper 95% CI
	\$36K–\$60K	Biology, chemistry, and physics	20.78	0.04	20.70	20.86
	\$60K–\$100K	Biology, chemistry, and physics	21.40	0.04	21.33	21.47
	>\$100K	Biology, chemistry, and physics	21.96	0.03	21.90	22.02
	<\$36K	Other 3 yr combinations	19.38	0.06	19.25	19.50
	\$36K–\$60K	Other 3 yr combinations	20.06	0.07	19.91	20.20
	\$60K–\$100K	Other 3 yr combinations	20.58	0.07	20.45	20.71
	>\$100K	Other 3 yr combinations	21.13	0.05	21.03	21.23
Social studies	<\$36K	Other less than 3 yr combinations	19.74	0.04	19.67	19.82
	\$36K–\$60K	Other less than 3 yr combinations	20.45	0.05	20.36	20.54
	\$60K–\$100K	Other less than 3 yr combinations	20.98	0.04	20.90	21.06
	>\$100K	Other less than 3 yr combinations	21.59	0.04	21.52	21.65
	<\$36K	U.S. hist., world hist., and Am. gov.	19.61	0.05	19.51	19.71
	\$36K–\$60K	U.S. hist., world hist., and Am. gov.	20.22	0.06	20.10	20.33
	\$60K–\$100K	U.S. hist., world hist., and Am. gov.	20.58	0.05	20.47	20.68
	>\$100K	U.S. hist., world hist., and Am. gov.	21.02	0.04	20.94	21.11
	<\$36K	U.S. hist., world hist., Am. gov., and other history	19.47	0.10	19.28	19.67
	\$36K–\$60K	U.S. hist., world hist., Am. gov., and other history	20.13	0.10	19.93	20.33
	\$60K–\$100K	U.S. hist., world hist., Am. gov., and other history	20.49	0.09	20.31	20.66
	>\$100K	U.S. hist., world hist., Am. gov., and other history	20.89	0.07	20.77	21.02
	<\$36K	Other 3 to 3.5 yr combinations	19.66	0.04	19.58	19.75
	\$36K–\$60K	Other 3 to 3.5 yr combinations	20.30	0.05	20.21	20.40
	\$60K–\$100K	Other 3 to 3.5 yr combinations	20.67	0.05	20.58	20.76
	>\$100K	Other 3 to 3.5 yr combinations	21.14	0.04	21.07	21.22
	<\$36K	Other 4+ yr combinations	19.46	0.05	19.37	19.55
	\$36K–\$60K	Other 4+ yr combinations	20.07	0.05	19.96	20.17
	\$60K–\$100K	Other 4+ yr combinations	20.53	0.05	20.43	20.63
	>\$100K	Other 4+ yr combinations	20.78	0.04	20.70	20.86

Gradient-Boosted Machine Model Results

The two GBM models, Models 5 and 6, included all predictors in Model 1, and Model 6 also included the three demographic predictors. As was mentioned previously, although the interactions are not explicitly declared in the GBM models, the GBM models inherently account for interactions, in this case up to a seven-way interaction. Again, a grid of hyperparameters was tested to identify the best tuning parameters for the GBM models. For both models, these parameters were 1,500 trees, an interaction depth of seven, a shrinkage parameter of 0.1, and a minimum number of observations per node of 20.

GBM models do not provide coefficients that are provided by traditional models, such as those provided in the appendix for the HLMs, but we can examine feature (i.e., predictor) importance. In the first GBM model (Figure 5), we can see that HSGPA is by far the strongest predictor of ACTC score. This is followed distantly by advanced math coursework, the percentage of students at a school meeting poverty guidelines, math course-taking, having taken advanced coursework in social studies, the percentage of White students at a school, having taken advanced coursework in science and English, science course-taking, the number of AP courses offered at a school, and finally by having taken social studies coursework. These final two predictors seem to have had negligible impact on the prediction of ACTC scores.

Figure 5. Feature Importance for the Gradient-Boosted Machine Model Without Demographics

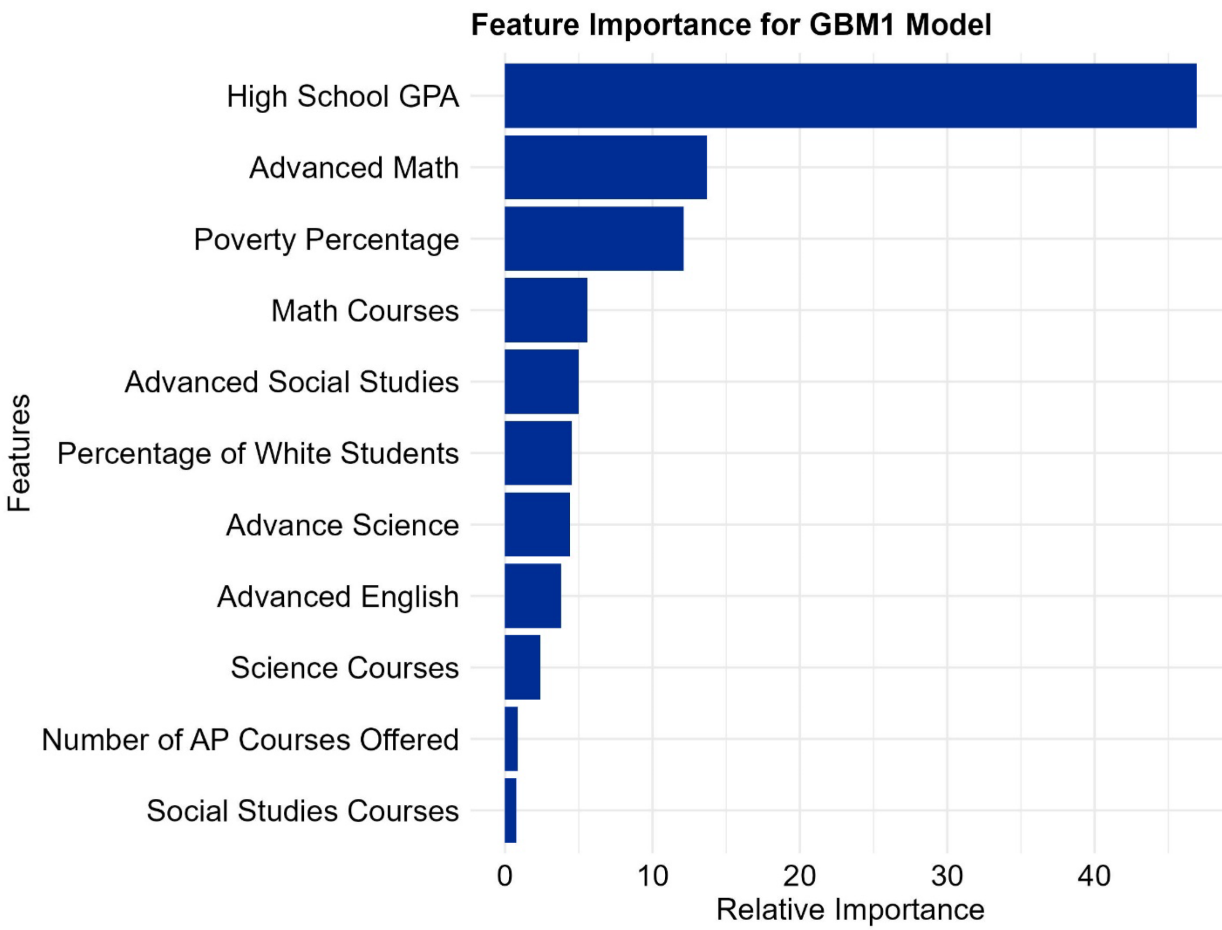


Table 6 presents the partial dependence plot results, which show the estimated marginal means of ACTC score based on different course-taking patterns in social studies, math, and science.

This methodology predicts ACTC score and then averages predictions across coursework pattern, which allows an understanding of how a single predictor (in this case coursework) affects the outcome.

Table 6. Estimated Marginal Means for Coursework Taken for Model 5

Subject	Coursework	Estimated mean
Social studies	Other less than 3 yr combinations	21.09
	U.S. hist., world hist., and Am. gov.	20.35
	U.S. hist., world hist., Am. gov., and other history	20.98
	Other 3 to 3.5 yr combinations	21.48
	Other 4+ yr combinations	21.40
Math	Less than Algebra I, geometry, and Algebra II	16.30
	Algebra I, geometry, and Algebra II	19.12
	Beyond Algebra II	23.30
	Other math patterns	22.02
Science	Other less than 3 yr combinations	20.22
	General science	17.13
	Biology	17.66
	Biology and chemistry	21.31
	Biology, chemistry, and physics	23.30
	Other 3 yr combinations	19.79

In Figure 6, we can see that, once again, HSGPA was far and away the most important predictor of ACTC scores. HSGPA was distantly followed by taking advanced coursework in math, the percentage of students at a school meeting poverty guidelines, family income, math coursework, race/ethnicity, taking advanced coursework in social studies, taking advanced coursework in science, taking advanced coursework in English, the percentage of White students at a school, science coursework, gender, the number of AP courses offered at a school, and social studies coursework. It is worth noting that there are three predictors that emerged as more important for the prediction of ACTC scores than any student demographic characteristic: HSGPA, taking advanced coursework in math, and the percentage of students at a school meeting poverty guidelines. Of these three, two predictors are in the student’s direct control.

Figure 6. Feature Importance for the Gradient-Boosted Machine Model With Demographics

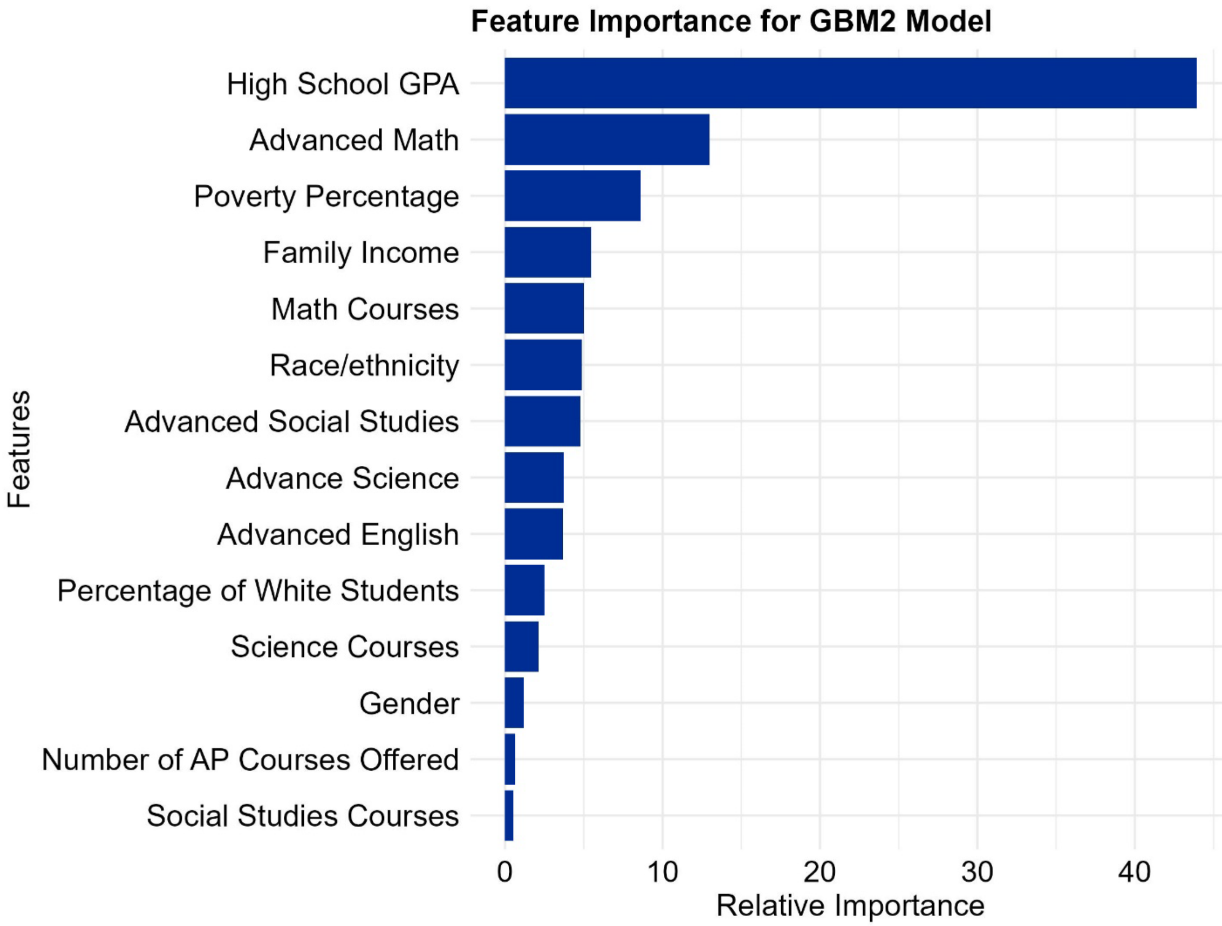


Table 7 presents the estimated ACTC score by coursework and student demographic characteristic.

Table 7. Estimated Marginal Means for Coursework Taken for Model 6 by Student Demographics

Subject	Characteristic	Coursework	Estimated Mean
Social studies	Male	Other less than 3 yr combinations	21.28
	Female	Other less than 3 yr combinations	20.92
	Male	U.S. hist., world hist., and Am. gov.	21.74
	Female	U.S. hist., world hist., and Am. gov.	21.28
	Male	U.S. hist., world hist., Am. gov., and other history	20.64
	Female	U.S. hist., world hist., Am. gov., and other history	20.07
	Male	Other 3 to 3.5 yr combinations	21.59
	Female	Other 3 to 3.5 yr combinations	21.28
	Male	Other 4+ yr combinations	21.04
	Female	Other 4+ yr combinations	21.28

Math	Male	Less than Alg. I, geom., and Alg. II	16.18
	Female	Less than Alg. I, geom., and Alg. II	16.42
	Male	Alg. I, geom., and Alg. II	19.14
	Female	Alg. I, geom., and Alg. II	19.11
	Male	Beyond Algebra II	23.76
	Female	Beyond Algebra II	22.94
	Male	Other math patterns	22.32
	Female	Other math patterns	21.74
Science	Male	Other less than 3 yr combinations	20.58
	Female	Other less than 3 yr combinations	19.84
	Male	General science	17.10
	Female	General science	17.18
	Male	Biology	17.50
	Female	Biology	17.80
	Male	Biology and chemistry	23.74
	Female	Biology and chemistry	22.84
	Male	Biology, chemistry, and physics	21.39
	Female	Biology, chemistry, and physics	21.25
	Male	Other 3 yr combinations	20.16
	Female	Other 3 yr combinations	19.33
Social studies	White	Other less than 3 yr combinations	21.88
	African American	Other less than 3 yr combinations	16.74
	Two or more / American Indian / Native Hawaiian	Other less than 3 yr combinations	20.71
	Hispanic	Other less than 3 yr combinations	18.88
	Asian	Other less than 3 yr combinations	26.02
	Prefer not to respond / Missing	Other less than 3 yr combinations	22.69
	White	U.S. hist., world hist., and Am. gov.	20.98
	African American	U.S. hist., world hist., and Am. gov.	16.66
	Two or more / American Indian / Native Hawaiian	U.S. hist., world hist., and Am. gov.	19.83
	Hispanic	U.S. hist., world hist., and Am. gov.	18.62
	Asian	U.S. hist., world hist., and Am. gov.	24.35
	Prefer not to respond / Missing	U.S. hist., world hist., and Am. gov.	21.15
	White	U.S. hist., world hist., Am. gov., and other history	21.63
	African American	U.S. hist., world hist., Am. gov., and other history	17.14
	Two or more / American Indian / Native Hawaiian	U.S. hist., world hist., Am. gov., and other history	20.17
	Hispanic	U.S. hist., world hist., Am. gov., and other history	19.22
	Asian	U.S. hist., world hist., Am. gov., and other history	24.99

	Prefer not to respond / Missing	U.S. hist., world hist., Am. gov., and other	22.38
	White	Other 3 to 3.5 yr combinations	22.18
	African American	Other 3 to 3.5 yr combinations	17.69
	Two or more / American Indian / Native Hawaiian	Other 3 to 3.5 yr combinations	21.05
	Hispanic	Other 3 to 3.5 yr combinations	19.72
	Asian	Other 3 to 3.5 yr combinations	25.50
	Prefer not to respond / Missing	Other 3 to 3.5 yr combinations	22.62
	White	Other 4+ yr combinations	22.19
	African American	Other 4+ yr combinations	17.95
	Two or more / American Indian / Native Hawaiian	Other 4+ yr combinations	21.06
	Hispanic	Other 4+ yr combinations	20.06
	Asian	Other 4+ yr combinations	24.88
	Prefer not to respond / Missing	Other 4+ yr combinations	22.15
Math	White	Less than Alg. I, geom., and Alg. II	17.00
	African American	Less than Alg. I, geom., and Alg. II	14.76
	Two or more / American Indian / Native Hawaiian	Less than Alg. I, geom., and Alg. II	16.16
	Hispanic	Less than Alg. I, geom., and Alg. II	15.47
	Asian	Less than Alg. I, geom., and Alg. II	18.43
	Prefer not to respond / Missing	Less than Alg. I, geom., and Alg. II	16.69
	White	Alg. I, geom., and Alg. II	19.85
	African American	Alg. I, geom., and Alg. II	16.38
	Two or more / American Indian / Native Hawaiian	Alg. I, geom., and Alg. II	18.76
	Hispanic	Alg. I, geom., and Alg. II	17.82
	Asian	Alg. I, geom., and Alg. II	21.54
	Prefer not to respond / Missing	Alg. I, geom., and Alg. II	19.93
	White	Beyond Algebra II	23.88
	African American	Beyond Algebra II	18.82
	Two or more / American Indian / Native Hawaiian	Beyond Algebra II	23.19
	Hispanic	Beyond Algebra II	21.24
	Asian	Beyond Algebra II	27.02
	Prefer not to respond / Missing	Beyond Algebra II	24.59
	White	Other math patterns	23.06
	African American	Other math patterns	17.73
	Two or more / American Indian / Native Hawaiian	Other math patterns	21.68
	Hispanic	Other math patterns	19.89
	Asian	Other math patterns	26.16

	Prefer not to respond / Missing	Other math patterns	22.47
Science	White	Other less than 3 yr combinations	21.31
	African American	Other less than 3 yr combinations	15.83
	Two or more / American Indian / Native Hawaiian	Other less than 3 yr combinations	19.93
	Hispanic	Other less than 3 yr combinations	18.07
	Asian	Other less than 3 yr combinations	25.31
	Prefer not to respond / Missing	Other less than 3 yr combinations	22.80
	White	General science	17.94
	African American	General science	14.92
	Two or more / American Indian / Native Hawaiian	General science	17.03
	Hispanic	General science	15.82
	Asian	General science	22.37
	Prefer not to respond / Missing	General science	16.56
	White	Biology	18.38
	African American	Biology	15.34
	Two or more / American Indian / Native Hawaiian	Biology	17.57
	Hispanic	Biology	16.58
	Asian	Biology	20.29
	Prefer not to respond / Missing	Biology	17.90
	White	Biology and chemistry	21.99
	African American	Biology and chemistry	17.70
	Two or more / American Indian / Native Hawaiian	Biology and chemistry	20.93
	Hispanic	Biology and chemistry	19.54
	Asian	Biology and chemistry	24.78
	Prefer not to respond / Missing	Biology and chemistry	22.40
	White	Biology, chemistry, and physics	24.15
	African American	Biology, chemistry, and physics	18.66
	Two or more / American Indian / Native Hawaiian	Biology, chemistry, and physics	23.31
	Hispanic	Biology, chemistry, and physics	20.59
	Asian	Biology, chemistry, and physics	26.94
	Prefer not to respond / Missing	Biology, chemistry, and physics	24.58
	White	Other 3 yr combinations	20.76
	African American	Other 3 yr combinations	15.66
	Two or more / American Indian / Native Hawaiian	Other 3 yr combinations	19.65
	Hispanic	Other 3 yr combinations	18.04
	Asian	Other 3 yr combinations	24.60

	Prefer not to respond / Missing	Other 3 yr combinations	20.17
Social studies	<$36K	Other less than 3 yr combinations	17.00
	$36K–$60K	Other less than 3 yr combinations	18.99
	$60K–$100K	Other less than 3 yr combinations	20.77
	>$100K	Other less than 3 yr combinations	23.73
	<$36K	U.S. hist., world hist., and Am. gov.	17.02
	$36K–$60K	U.S. hist., world hist., and Am. gov.	18.72
	$60K–$100K	U.S. hist., world hist., and Am. gov.	20.25
	>$100K	U.S. hist., world hist., and Am. gov.	22.69
	<$36K	U.S. hist., world hist., Am. gov., and other history	17.56
	$36K–$60K	U.S. hist., world hist., Am. gov., and other history	19.33
	$60K–$100K	U.S. hist., world hist., Am. gov., and other history	20.74
	>$100K	U.S. hist., world hist., Am. gov., and other history	22.89
	<$36K	Other 3 to 3.5 yr combinations	18.09
	$36K–$60K	Other 3 to 3.5 yr combinations	19.73
	$60K–$100K	Other 3 to 3.5 yr combinations	21.31
	>$100K	Other 3 to 3.5 yr combinations	23.49
	<$36K	Other 4+ yr combinations	18.35
	$36K–$60K	Other 4+ yr combinations	20.00
	$60K–$100K	Other 4+ yr combinations	21.49
	>$100K	Other 4+ yr combinations	23.21
Math	<$36K	Less than Alg. I, geom., and Alg. II	14.93
	$36K–$60K	Less than Alg. I, geom., and Alg. II	15.94
	$60K–$100K	Less than Alg. I, geom., and Alg. II	16.87
	>$100K	Less than Alg. I, geom., and Alg. II	18.33
	<$36K	Alg. I, geom., and Alg. II	16.77
	$36K–$60K	Alg. I, geom., and Alg. II	18.08
	$60K–$100K	Alg. I, geom., and Alg. II	19.27
	>$100K	Alg. I, geom., and Alg. II	20.99
	<$36K	Beyond Algebra II	19.52
	$36K–$60K	Beyond Algebra II	21.29
	$60K–$100K	Beyond Algebra II	22.80
	>$100K	Beyond Algebra II	24.97
	<$36K	Other math patterns	17.84
	$36K–$60K	Other math patterns	19.94
	$60K–$100K	Other math patterns	21.84
	>$100K	Other math patterns	24.56
Science	<$36K	Other less than 3 yr combinations	16.14
	$36K–$60K	Other less than 3 yr combinations	18.33
	$60K–$100K	Other less than 3 yr combinations	20.42

>$100K	Other less than 3 yr combinations	23.79
<$36K	General science	15.37
$36K–$60K	General science	16.52
$60K–$100K	General science	17.59
>$100K	General science	19.39
<$36K	Biology	16.56
$36K–$60K	Biology	15.87
$60K–$100K	Biology	17.16
>$100K	Biology	18.20
<$36K	Biology and chemistry	18.11
$36K–$60K	Biology and chemistry	19.74
$60K–$100K	Biology and chemistry	21.14
>$100K	Biology and chemistry	23.15
<$36K	Biology, chemistry, and physics	18.86
$36K–$60K	Biology, chemistry, and physics	20.94
$60K–$100K	Biology, chemistry, and physics	22.79
>$100K	Biology, chemistry, and physics	25.17
<$36K	Other 3 yr combinations	16.43
$36K–$60K	Other 3 yr combinations	18.26
$60K–$100K	Other 3 yr combinations	20.08
>$100K	Other 3 yr combinations	22.64

Does Increased Course-Taking in Mathematics and Science Predict ACT Performance When Models Account for Other Academic and School Characteristics?

The strongest positive predictors of ACTC scores in Model 1 were taking mathematics beyond Algebra II, taking advanced coursework in math, taking other unidentified math patterns, and HSGPA (Figure 1). The strongest negative predictor of ACT Composite score was the percentage of students who met poverty guidelines at a school. This highlights the important role that high school coursework plays in ACT performance.

Table 2 shows the estimated marginal ACTC score means for students taking different coursework patterns. In general, we can see that taking additional mathematics and science coursework is associated with higher ACTC scores. There was very little difference between mean ACTC scores across social studies coursework taken.

In the GBM model without demographics, Model 5 (Table 6), taking math courses beyond Algebra II resulted in the highest estimated ACTC scores. Students who took less than Algebra I, geometry, and Algebra II had lower estimated ACTC scores than did students who took other math patterns. Students taking biology, chemistry, and physics had the highest estimated ACTC scores. We can also see that additional science coursework was associated with an incremental increase in ACTC scores. Within one point, all social studies coursework patterns had a similar estimated ACTC score.

Do Student Demographics (Gender, Race/Ethnicity, and Family Income) Moderate the Relationship Between Course-Taking and ACT Performance?

In Model 2, HSGPA is a very strong predictor of ACTC score, reaffirming its importance in academic achievement (Figure 2). Advanced coursework in English and math, taking math beyond Algebra II, and taking other math patterns also showed a strong positive relationship with ACTC scores. In fact, taking math beyond Algebra II had the largest positive coefficient in the model. The percentage of students meeting poverty guidelines remained a strong negative predictor of ACTC scores. For both math and science, female students had lower estimated ACTC scores than male students who took the same courses. For social studies, the interaction terms with gender tended to be small and non-significant.

In Model 3 (Figure 3), we can see that once again HSGPA, taking advanced coursework in math, taking math beyond Algebra II, and taking other math patterns had a strong positive relationship with ACTC scores. The relationship between the percentage of students at a school meeting poverty guidelines remains significant and negative. The main effects for African American students, Hispanic students, and students from the two or more races / American Indian / Native Hawaiian group are also significantly negatively related to ACTC scores. African American and Hispanic students had lower ACTC scores than White students across all math coursework patterns examined. Asian students, however, had a higher estimated ACTC score when they took math beyond Algebra II and other unidentified math patterns.

Generally speaking, across all coursework groups, White and Asian students had the highest estimated ACTC scores, while African American and Hispanic students had the lowest estimated ACTC scores (Table 4). This pattern can be seen in math, science, and social studies, which suggests there may be systematic differences in educational preparation or other contributing factors. This gap remains even when we look at higher levels of course-taking, such as taking math beyond Algebra II and taking biology, chemistry, and physics. It is important to note that the documentation of differences between racial/ethnic groups is not in and of itself evidence of unfairness in the ACT.

In Model 4 (Figure 4), HSGPA, taking advanced coursework in math, taking mathematics coursework beyond Algebra II, the number of AP courses offered at a school, and the percentage of White students at a school all had positive impacts on ACTC scores. In general, higher family income was positively associated with higher estimated ACTC scores across all subjects examined (Table 5). Across math, science, and social studies, students from higher-income families consistently had higher estimated ACTC scores than students from lower-income families. Furthermore, the largest gaps appeared to be in advanced coursework categories, where students from families earning $100,000 or more had significantly higher ACTC scores than students from families earning less than $36,000. For example, among students taking Algebra I, geometry, and Algebra II, students from families of less than $36,000 had an estimated 19.45 ACTC score, while students from families of over $100,000 had an estimated 20.36 ACTC score. Similarly, students taking mathematics coursework beyond

Algebra II ranged in ACTC score from 20.16 for students from families with less than $36,000 to 22.14 for students from families with over $100,000. Additionally, for students who took biology, chemistry, and physics (the most advanced science coursework pattern), scores ranged from 20.01 for students from families with $36,000 or less to 21.96 for students from families with over $100,000. This suggests that students from higher family incomes benefit more from taking more advanced coursework or that additional factors outside the scope of this study contribute to the success of students from higher-income families.

It is also worth noting that the gap between income groups is smaller at lower-level coursework and widens as coursework difficulty increases. For example, the smallest gap in science is seen in the only-biology coursework, where low-income students were just 0.6 points behind high-income students; in mathematics coursework, the largest gap—of almost 2 points—was seen in the “beyond Algebra II” category between students from families with less than $36,000 income and students from families with more than $100,000 income. This suggests that while taking advanced coursework is important for all students, not all students benefit the same from taking advanced coursework. As was noted previously, differences in coursework efficacy among family income levels do not necessarily indicate unfairness in the ACT but more likely point to structural inequalities in the educational system.

Table 6 shows a clear pattern of increased estimated ACTC scores with additional math and science coursework. For example, in math, students who took less than Algebra I, geometry, and Algebra II had the lowest estimated ACTC score (16.30), and students who took math beyond Algebra II had the highest estimated ACTC score (23.30). The pattern is similar with science: Students who took only general science had the lowest estimated ACTC score at 17.13, while students who took biology, chemistry, and physics had the highest estimated ACTC score at 23.30. Most social studies coursework patterns were associated with an estimated ACTC score of about 21.

Table 7 shows the estimated ACTC scores from Model 6, the GBM model with demographics. We can see from this table that there are slight gender differences between males and females in social studies, math, and science, with male students generally scoring slightly higher than female students, particularly in advanced coursework. As an example, in social studies, male students scored 21.28, while female students scored 20.92 in the “other less than 3 yr combinations” category. In math, while male students scored an estimated 23.76, female students scored an estimated 22.94 ACTC score in the “beyond Algebra II” category. There were also significant racial gaps found in ACTC score estimates. Asian and White students consistently achieved the highest estimated ACTC scores, while African American and Hispanic students tended to achieve the lowest. This was true across all course-taking patterns. Family income also played an important role in differentiating estimated ACTC scores, as students from higher-income households tended to have higher ACTC scores across all subjects and coursework levels.

Can Modern Machine Learning Models, Such as Gradient-Boosted Machines, Improve the Prediction of ACT Performance Over Traditional Regression Methods?

In order to evaluate whether the GBM models improved the prediction of ACTC score over traditional HLM regression methods, I compared all the models. Models 1 and 5 are a direct comparison with the same predictors. Because of the complexity of attempting a HLM that included all three demographics and their interactions with math, science, and social studies course-taking patterns, I elected to run Models 2, 3, and 4, which look at one demographic characteristic at a time.

To evaluate the functioning of the models, I examined the root mean square error (RMSE) and mean absolute error (MAE) across models. RMSE measures the square root of the average squared deviations between the predicted and actual ACTC scores. This calculation gives more weight to larger errors and is useful for penalizing larger errors more heavily. The formula for RMSE is

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}.$$

MAE, on the other hand, measures the average of the absolute differences between the predicted and actual ACTC scores. In this calculation, all errors are treated equally, which gives a clear perspective of the average error magnitude. The formula for MAE is

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|.$$

Due to the slight differences in the calculations of these two equations, RMSE highlights a few very large prediction errors, while MAE gives a sense of the average error across all predictions. Models 2, 3, and 4 slightly improved predictions of ACTC score over Model 1 (i.e., considering demographics helps ACTC score prediction in HLMs). Comparing Models 1 and 5, we see that the GBM model without demographics did not appreciably improve the predictions of ACTC scores. Model 6 was, however, slightly better at predicting ACTC scores than the other models. This raises the question of whether the joint consideration of all three demographic factors is what is helping the GBM model with demographics provide better predictions.

Table 8. RMSE and MAE for all Models

Model	RMSE	MAE
Linear mixed model (Model 1)	3.65	2.90
Linear mixed model with gender (Model 2)	3.62	2.88
Linear mixed model with race/ethnicity (Model 3)	3.59	2.86
Linear mixed model with family income (Model 4)	3.62	2.88
GBM model without demographics (Model 5)	3.67	2.90
GBM model with demographics (Model 6)	3.56	2.82

To answer this question, I ran a seventh HLM with all three demographic characteristics and their interaction with course-taking pattern.[3] The RMSE and MAE for this new model were 3.55 and 2.82. In this comparison of the new model and Model 6, there is no appreciable difference in the accuracy of predictions of ACTC score. Therefore, if we are willing to accept the complexity of a HLM with 138 unique coefficients, we could conclude that GBM models did not improve ACTC score predictions. However, practical concerns with this model, such as the difficulty in explaining the results, may make the GBM model a more attractive option.

Discussion

The present study provides additional empirical support for the longstanding understanding that rigorous high school coursework, particularly in math and science, significantly and positively impacts ACT Composite scores. Like previous research (Harwell et al., 2016; Noble & McNabb, 1989; Radunzel & Noble, 2012), this study confirmed that students who take advanced coursework in mathematics and science tend to perform better on the ACT. This is consistent with Sanchez (2025), which shows that the rigor and quantity of high school coursework in mathematics, science, and English significantly affect ACT ELA and STEM Benchmark attainment. Students who take advanced courses, study subjects for more years, and maintain higher GPAs are more likely to meet these Benchmarks. In addition to revalidating this finding, this study also extends prior work by looking at modern statistical techniques, including both hierarchical linear modeling and machine learning–based gradient-boosted machines to help provide a more nuanced understanding of the student factors impacting ACTC scores.

This study demonstrated that the strongest predictors of ACTC performance were HSGPA, completion of mathematics coursework beyond Algebra II, and taking advanced coursework in math. While weaker as predictors, taking advanced coursework in English, social studies, and science; taking Algebra I, geometry, and Algebra II; and taking biology, chemistry, and physics were all positively associated with ACTC scores. This is in line with the previous findings by Schiel et al. (1996) and Laing et al. (1987) that indicated that STEM coursework has a strong influence on standardized test performance. This research study also showed that social studies coursework had a much smaller impact on ACTC scores, which in itself emphasizes the role of STEM education in shaping college readiness. Recall that in this study, I did not use English course-taking patterns because the vast majority of students in the sample had taken English 9, 10, and 11 at the time of testing.

While the study clearly demonstrated that rigorous coursework was important and that it was beneficial across all student subgroups, not all subgroups benefited equally. Gender disparities were found in both the HLMs and the GBM models for math and science performance, with male students tending to score higher than female students on the ACT despite similar coursework patterns. This is consistent with the gender differences that have been found on the ACT in previous research (McNeish et al., 2015; Noble & McNabb, 1989;) and suggests that

[3] Due to the complexities of this model, the model results are not presented in the paper but can be obtained from the author.

additional interventions may be necessary to support female students in STEM-related coursework.

Race/ethnicity was also found to moderate the relationship between coursework taken and ACTC scores. In the HLMs and the GBM models, White and Asian students consistently outperformed their African American and Hispanic peers, even after the models controlled for course-taking patterns. This finding, too, is consistent with previous research (Riegle-Crumb & Grodsky, 2010), which indicates that structural inequalities in education may be affecting student outcomes.

Family income was an additional factor influencing ACTC scores, with higher-income students consistently outperforming their lower-income peers in the HLMs and the GBM models. This gap was particularly pronounced in advanced course-taking patterns, where high-income students showed significantly higher ACTC scores. This highlights how important it is to consider family income and its role in shaping educational opportunities and test performance, likely due to differences in access to quality instruction, academic resources, tutoring, etc.

One of the key contributions of this particular study was a comparison between traditional hierarchical linear models and gradient-boosted machine models. While this study did find that the GBM models offered a slight improvement in predictive accuracy, the difference is likely not practically significant. The GBM model that incorporated demographic variables performed marginally better than most of the HLMs, but a highly complex HLM with all demographic interactions resulted in nearly identical predictive accuracy. The most complex HLM examined would require large sample sizes such as those used in this study, while GBM models have shown promise with smaller sample sizes; however, GBM models are more reliable and robust with larger sample sizes. The most significant practical difference in this analysis was that the HLMs could be run in minutes, while the GBM models took several hours to complete calculations. This suggests that while machine learning methods offer valuable tools for educational research, traditional regression approaches remain very effective for predicting student outcomes.

There are important implications of this research that should be called out. First, this study reinforces how important it is to promote rigorous coursework in math and science as a strategy for helping students improve college readiness. This also provides a call to high schools to strengthen and expand their STEM course offerings and, additionally, provide additional supports to students who may be struggling in these subjects. Second, the gaps identified by student demographics highlight the need for a fairness lens to be placed on interventions. The gaps in ACTC performance by student demographics suggest that rigorous coursework alone is not enough to close achievement gaps. Educators and policymakers should explore the use of additional supports such as targeted tutoring and mentoring, and they should help make test preparation resources available to all students. Finally, this study shows that while machine learning techniques can provide valuable insights, traditional statistical models remain a strong choice for predicting student outcomes. If educational researchers want to use advanced machine learning models, they need to carefully weigh the tradeoffs between predictive accuracy and interpretability (particularly in terms of explaining the models to student and parent stakeholders) when selecting the analytical approach that best meets their needs.

Limitations

Despite this study providing valuable information as an update to previous research and an extension into new methodologies, there are several limitations to be noted. First, while the study sample itself was large and representative of the population (see Table 1), it was limited to students from a single southern state; this potentially limits the generalizability of these findings. Additionally, I combined data for those identifying as American Indian / Alaska Native (0.8%), Native Hawaiian / Pacific Islander (0.2%), and two or more races (5.1%). This necessarily limits what we can conclude about these student demographic groups. Furthermore, this study uses self-reported coursework data, which may introduce student uncertainty in reporting. For example, students may overestimate their HSGPA or misreport their academic history. If possible, it would be useful to replicate this study using transcript grades and coursework data. This study primarily concerned itself with the impact of student characteristics and student outcomes that were within the control of the student, while using some school characteristics as control variables. Future research should explore the impact of school-level characteristics such as teacher quality and curriculum rigor.

References

Camara, W., Kimmel, E., Scheuneman, J., & Sawtell, E. A. (2003). *Whose grades are inflated?* (Research Report No. 2003-4). College Board. https://files.eric.ed.gov/fulltext/ED563203.pdf

Harwell, M. R., Moreno, M., & Post, T. (2016). A study of the relationship between the ACT college mathematics readiness standard and college mathematics achievement. *Journal of Psychoeducational Assessment*, *34*(3), 269–281. https://journals.sagepub.com/doi/pdf/10.1177/0734282915594069

Kuncel, N. R., Credé, M., & Thomas, L. L. (2005). The validity of self-reported grade point averages, class ranks, and test scores: A meta-analysis and review of the literature. *Review of Educational Research*, *75*(1), 63–82. https://doi.org/10.3102/00346543075001063

Laing, J., Engen, H., & Maxey, J. (1987). *Relationships between ACT test scores and high school courses* [Paper presentation]. American Association for Counseling and Development Annual Meeting, New Orleans, LA, United States. https://files.eric.ed.gov/fulltext/ED283103.pdf

McFarland, J., Hussar, B., Zhang, J., Wang, X., Wang, K., Hein, S., Diliberti, M., Forrest Cataldi, E., Bullock Mann, F., & Barmer, A. (2019). *The condition of education 2019* (NCES Report No. 2019-144). U.S. Department of Education: National Center for Education Statistics. https://nces.ed.gov/pubs2019/2019144.pdf

McNeish, D. M., Radunzel, J., & Sanchez, E. (2015). *A multidimensional perspective of college readiness: Relating student and school characteristics to performance on the ACT* (Research Report No. 2015-6). ACT. https://files.eric.ed.gov/fulltext/ED563774.pdf

National Commission on Excellence in Education. (1983). *A nation at risk: The imperative for educational reform*. U.S. Department of Education. https://files.eric.ed.gov/fulltext/ED226006.pdf

Noble, J. P., Davenport, M., Schiel, J., & Pommerich, M. (1999). *Relationships between the noncognitive characteristics, high school course work and grades, and test scores for ACT-tested students* (Research Report Series 99-4). ACT. https://www.act.org/content/dam/act/unsecured/documents/ACT_RR99-04.pdf

Noble, J. P., & McNabb, T. (1989). *Differential coursework and grades in high school: Implications for performance on the ACT assessment* (Research Report No. 89-5). ACT. https://files.eric.ed.gov/fulltext/ED322159.pdf

Radunzel, J., & Noble, J. (2012). *Predicting long-term college success through degree completion using ACT Composite score, ACT Benchmarks, and high school grade point average* (Research Report No. 2012-5). ACT. https://www.act.org/content/dam/act/unsecured/documents/ACT_RR2012-5.pdf

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (2nd ed.). Sage Publications. https://collegepublishing.sagepub.com/products/hierarchical-linear-models-2-9230

Riegle-Crumb, C., & Grodsky, E. (2010). Racial-ethnic differences at the intersection of math course-taking and achievement. *Sociology of Education*, *83*(3), 248–270. https://doi.org/10.1177/0038040710375689

Sanchez, E. I. (2025). *Predicting ACT ELA and STEM Benchmark attainment: The role of high school coursework and grades.* ACT.

Sanchez, E. I., & Buddin, R. (2016). *How accurate are self-reported high school courses, course grades, and grade point average?* (Research Report No. 2016-3). https://www.act.org/content/dam/act/unsecured/documents/5269-research-report-how-accurate-are-self-reported-hs-courses.pdf

Schiel, J., Pommerich, M., & Noble, J. P. (1996). *Factors associated with longitudinal educational achievement, as measured by PLAN and ACT assessment scores* (Research Report No. 96-5). ACT. https://www.act.org/content/dam/act/unsecured/documents/ACT_RR96-05.pdf

Shaw, E. J., & Mattern, K. D. (2009). *Examining the accuracy of self-reported high school grade point average* (Research Report No. 2009-5). College Board. https://files.eric.ed.gov/fulltext/ED562616.pdf

Appendix

Table A1. Model 1 Standardized Coefficients

Predictor	Standardized coefficient
HSGPA	1.637*** (0.007)
Advanced English	0.979*** (0.016)
Advanced social studies	0.840*** (0.016)
Advanced math	1.703*** (0.017)
Advanced science	0.744*** (0.017)
Social studies: U.S. history, world history, and American government	−0.394*** (0.021)
Social studies: U.S. history, world history, American government, and other	−0.505*** (0.040)
Social studies: Other 3–3.5 yr combinations	−0.320*** (0.015)
Social studies: Other 4+ yr combinations	−0.605*** (0.018)
Math: Algebra I, geometry, and Algebra II	0.471*** (0.024)
Math: Beyond Algebra II	1.864*** (0.025)
Math: Other patterns	1.586*** (0.035)
Science: Less than 3 yr	−0.551*** (0.090)
Science: Biology	−0.742*** (0.045)
Science: Biology and chemistry	−0.176*** (0.043)
Science: Biology, chemistry, and physics	0.585*** (0.044)
Science: Other 3 yr combinations	−0.314*** (0.051)
Percent poverty	−1.028*** (0.019)
AP courses taken	0.127*** (0.017)
Percent White	0.479*** (0.017)
Constant	18.013*** (0.050)
Observations	453,439
Log likelihood	−1,245,182.00
Akaike inf. crit.	2,490,410.00
Bayesian inf. crit.	2,490,664.00

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Tabel A2. Model 2 Standardized Coefficients

Predictor	Standardized coefficient
HSGPA	1.703*** (0.007)
Advanced English	1.108*** (0.016)
Advanced social studies	0.848*** (0.016)
Advanced math	1.614*** (0.017)
Advanced science	0.755*** (0.017)
Social studies: U.S. history, world history, and American government	−0.388*** (0.028)
Social studies: U.S. history, world history, American government, and other	−0.657*** (0.054)
Social studies: Other 3–3.5 yr combinations	−0.251*** (0.021)
Social studies: Other 4+ yr combinations	−0.613*** (0.026)
Math: Algebra I, geometry, and Algebra II	0.602*** (0.034)
Math: Beyond Algebra II	1.990*** (0.035)
Math: Other patterns	1.664*** (0.048)
Science: Less than 3 yr	−0.690*** (0.122)
Science: Biology	−0.813*** (0.061)
Science: Biology and chemistry	−0.179*** (0.059)
Science: Biology, chemistry, and physics	0.509*** (0.060)
Science: Other 3 yr combinations	−0.406*** (0.069)
Female	−0.886*** (0.090)
Percent poverty	−1.018*** (0.019)
AP courses taken	0.119*** (0.017)
Percent White	0.465*** (0.017)
Female * Social studies: U.S. history, world history, and American government	−0.039 (0.037)
Female * Social studies: U.S. history, world history, American government, and other	0.209*** (0.077)
Female * Social studies: Other 3–3.5 yr combinations	−0.026 (0.027)
Female * Social studies: Other 4+ yr combinations	0.133*** (0.033)
Female * Math: Algebra I, geometry, and Algebra II	−0.268*** (0.046)
Female * Math: Beyond Algebra II	−0.319*** (0.047)
Female * Math: Other patterns	−0.270*** (0.067)
Female * Science: Less than 3 yr	0.386** (0.177)
Female * Science: Biology	0.305*** (0.087)
Female * Science: Biology and chemistry	0.191** (0.084)
Female * Science: Biology, chemistry, and physics	0.073 (0.085)
Female * Science: Other 3 yr combinations	0.104 (0.100)
Constant	18.422*** (0.066)
Observations	453,439
Log likelihood	−1,241,475.000
Akaike inf. crit.	2,483,023.000
Bayesian inf. crit.	2,483,419.000

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Tabel A3. Model 3 Standardized Coefficients

Predictor	Standardized coefficient
HSGPA	1.556*** (0.007)
Advanced English	0.986*** (0.016)
Advanced social studies	0.818*** (0.016)
Advanced math	1.628*** (0.016)
Advanced science	0.724*** (0.016)
Social studies: U.S. history, world history, and American government	−0.368*** (0.025)
Social studies: U.S. history, world history, American government, and other	−0.469*** (0.048)
Social studies: Other 3–3.5 yr combinations	−0.295*** (0.018)
Social studies: Other 4+ yr combinations	−0.546*** (0.022)
Math: Algebra I, geometry, and Algebra II	0.583*** (0.031)
Math: Beyond Algebra II	2.033*** (0.033)
Math: Other patterns	1.871*** (0.045)
Science: General science	−0.687*** (0.118)
Science: Biology	−0.970*** (0.060)
Science: Biology and chemistry	−0.266*** (0.058)
Science: Biology, chemistry, and physics	0.575*** (0.059)
Science: Other 3 yr combinations	−0.305*** (0.067)
African American	−1.784*** (0.134)
Two or more / American Indian / Native Hawaiian	−0.473** (0.186)
Hispanic	−0.994*** (0.126)
Asian	−0.266 (0.216)
Prefer not to respond / Missing	0.166 (0.277)
Percent poverty	−0.931*** (0.018)
AP courses offered	0.108*** (0.016)
Percent White	0.180*** (0.017)
African American * Social studies: U.S. history, world history, and American government	0.179*** (0.062)
African American * Social studies: U.S. history, world history, American government, and other	0.138 (0.136)
African American * Social studies: Other 3–3.5 yr combinations	0.191*** (0.046)
African American * Social studies: Other 4+ yr combinations	0.221*** (0.052)
Two or more / American Indian / Native Hawaiian * Social studies: U.S. history, world history, and American government	−0.140* (0.079)
Two or more / American Indian / Native Hawaiian * Social studies: U.S. history, world history, American government, and other	−0.103 (0.145)
Two or more / American Indian / Native Hawaiian * Social studies: Other 3–3.5 yr combinations	−0.078 (0.059)
Two or more / American Indian / Native Hawaiian * Social studies: Other 4+ yr combinations	−0.150** (0.069)
Hispanic * Social studies: U.S. history, world history, and American government	0.106* (0.061)
Hispanic * Social studies: U.S. history, world history, American government, and other	0.057 (0.126)
Hispanic * Social studies: Other 3–3.5 yr combinations	0.031 (0.041)
Hispanic * Social studies: Other 4+ yr combinations	0.112** (0.049)
Asian * Social studies: U.S. history, world history, and American government	−0.683*** (0.096)
Asian * Social studies: U.S. history, world history, American government, and other	−0.742*** (0.223)
Asian * Social studies: Other 3–3.5 yr combinations	−0.382*** (0.061)
Asian * Social studies: Other 4+ yr combinations	−0.747*** (0.076)
Prefer not to respond / Missing * Social studies: U.S. history, world history, and American government	0.032 (0.142)

Prefer not to respond / Missing * Social studies: U.S. history, world history, American government, and other	0.037 (0.294)
Prefer not to respond / Missing * Social studies: Other 3–3.5 yr combinations	0.022 (0.101)
Prefer not to respond / Missing * Social studies: Other 4+ yr combinations	−0.176 (0.117)
African American * Math: Algebra I, geometry, and Algebra II	−0.430*** (0.064)
African American * Math: Beyond Algebra II	−1.328*** (0.068)
African American * Math: Other patterns	−1.333*** (0.098)
Two or more / American Indian / Native Hawaiian * Math: Algebra I, geometry, and Algebra II	−0.015 (0.093)
Two or more / American Indian / Native Hawaiian * Math: Beyond Algebra II	−0.084 (0.095)
Two or more / American Indian / Native Hawaiian * Math: Other patterns	−0.380*** (0.140)
Hispanic * Math: Algebra I, geometry, and Algebra II	−0.211*** (0.066)
Hispanic * Math: Beyond Algebra II	−0.545*** (0.068)
Hispanic * Math: Other patterns	−0.754*** (0.094)
Asian * Math: Algebra I, geometry, and Algebra II	0.523*** (0.160)
Asian * Math: Beyond Algebra II	1.701*** (0.157)
Asian * Math: Other patterns	1.653*** (0.183)
Prefer not to respond / Missing * Math: Algebra I, geometry, and Algebra II	0.250 (0.172)
Prefer not to respond / Missing * Math: Beyond Algebra II	0.546*** (0.172)
Prefer not to respond / Missing * Math: Other patterns	−0.221 (0.241)
African American * Science: General science	0.893*** (0.249)
African American * Science: Biology	1.016*** (0.131)
African American * Science: Biology and chemistry	0.533*** (0.128)
African American * Science: Biology, chemistry, and physics	−0.141 (0.131)
African American * Science: Other 3 yr combinations	0.035 (0.151)
Two or more / American Indian / Native Hawaiian * Science: General science	0.232 (0.353)
Two or more / American Indian / Native Hawaiian * Science: Biology	0.541*** (0.180)
Two or more / American Indian / Native Hawaiian * Science: Biology and chemistry	0.224 (0.175)
Two or more / American Indian / Native Hawaiian * Science: Biology, chemistry, and physics	0.310* (0.179)
Two or more / American Indian / Native Hawaiian * Science: Other 3 yr combinations	0.333 (0.207)
Hispanic * Science: General science	0.250 (0.260)
Hispanic * Science: Biology	0.549*** (0.122)
Hispanic * Science: Biology and chemistry	0.239** (0.117)
Hispanic * Science: Biology, chemistry, and physics	−0.124 (0.119)
Hispanic * Science: Other 3 yr combinations	0.073 (0.141)
Asian * Science: General science	−0.117 (0.548)
Asian * Science: Biology	−0.516*** (0.196)
Asian * Science: Biology and chemistry	−0.370** (0.167)
Asian * Science: Biology, chemistry, and physics	−0.172 (0.168)
Asian * Science: Other 3 yr combinations	−0.351* (0.213)
Prefer not to respond / Missing * Science: General science	−0.729 (0.595)
Prefer not to respond / Missing * Science: Biology	−0.558** (0.266)
Prefer not to respond / Missing * Science: Biology and chemistry	−0.732*** (0.249)
Prefer not to respond / Missing * Science: Biology, chemistry, and physics	−0.734*** (0.253)
Prefer not to respond / Missing * Science: Other 3 yr combinations	−1.443*** (0.313)
Constant	18.363*** (0.065)
Observations	453,439
Log likelihood	−1,238,186.000
Akaike inf. crit.	2,476,549.000
Bayesian inf. crit.	2,477,519.000

**p* < 0.1; ***p* < 0.05; ****p* < 0.01.

Tabel A4. Model 4 Standardized Coefficients

Predictor	Standardized coefficient
HSGPA	1.565*** (0.007)
Advanced English	0.959*** (0.016)
Advanced social studies	0.813*** (0.016)
Advanced math	1.630*** (0.017)
Advanced science	0.721*** (0.017)
Social studies: U.S. history, world history, and American government	−0.135*** (0.042)
Social studies: US History, world history, American government, and other	−0.270*** (0.096)
Social studies: Other 3–3.5 yr combinations	−0.079** (0.032)
Social studies: Other 4+ yr combinations	−0.286*** (0.039)
Math: Algebra I, geometry, and Algebra II	0.386*** (0.041)
Math: Beyond Algebra II	1.093*** (0.045)
Math: Other patterns	0.618*** (0.068)
Science: Less than 3 yr	−0.064 (0.158)
Science: Biology	0.068 (0.085)
Science: Biology and chemistry	0.382*** (0.083)
Science: Biology, chemistry, and physics	0.574*** (0.086)
Science: Other 3 yr combinations	−0.062 (0.099)
$36K–$60K	0.768*** (0.138)
$60K–$100K	1.084*** (0.133)
>$100K	1.770*** (0.116)
Percent poverty	−0.867*** (0.018)
AP courses offered	0.084*** (0.017)
Percent White	0.410*** (0.016)
$36K–$60K * Social studies: U.S. history, world history, and American government	−0.102* (0.062)
$36K–$60K * Social studies: U.S. history, world history, American government, and other	−0.054 (0.136)
$36K–$60K * Social studies: Other 3–3.5 yr combinations	−0.072 (0.047)
$36K–$60K * Social studies: Other 4+ yr combinations	−0.100* (0.055)
$60K–$100K * Social studies: U.S. history, world history, and American government	−0.269*** (0.057)
$60K–$100K * Social studies: U.S. history, world history, American government, and other	−0.221* (0.126)
$60K–$100K * Social studies: Other 3–3.5 yr combinations	−0.235*** (0.043)
$60K–$100K * Social studies: Other 4+ yr combinations	−0.165*** (0.051)
>$100K * Social studies: U.S. history, world history, and American government	−0.426*** (0.051)
>$100K * Social studies: U.S. history, world history, American government, and other	−0.422*** (0.112)
>$100K * Social studies: Other 3–3.5 yr combinations	−0.361*** (0.038)
>$100K * Social studies: Other 4+ yr combinations	−0.518*** (0.046)
$36K–$60K * Math: Algebra I, geometry, and Algebra II	0.105 (0.065)
$36K–$60K * Math: Beyond Algebra II	0.408*** (0.069)
$36K–$60K * Math: Other patterns	0.517*** (0.105)
$60K–$100K * Math: Algebra I, geometry, and Algebra II	0.210*** (0.065)
$60K–$100K * Math: Beyond Algebra II	0.789*** (0.068)
$60K–$100K * Math: Other patterns	1.061*** (0.100)
>$100K * Math: Algebra I, geometry, and Algebra II	0.210*** (0.061)
>$100K * Math: Beyond Algebra II	1.282*** (0.064)
>$100K * Math: Other patterns	1.690*** (0.090)
$36K–$60K * Science: Less than 3 yr	−0.307 (0.257)
$36K–$60K * Science: Biology	−0.630*** (0.135)
$36K–$60K * Science: Biology and chemistry	−0.493*** (0.132)

$36K–$60K * Science: Biology, chemistry, and physics	−0.194 (0.136)
$36K–$60K * Science: Other 3 yr combinations	−0.281* (0.156)
$60K–$100K * Science: Less than 3 yr	−0.459* (0.255)
$60K–$100K * Science: Biology	−0.867*** (0.128)
$60K–$100K * Science: Biology and chemistry	−0.601*** (0.126)
$60K–$100K * Science: Biology, chemistry, and physics	−0.037 (0.129)
$60K–$100K * Science: Other 3 yr combinations	−0.215 (0.148)
>$100K * Science: Less than 3 yr	−0.942*** (0.226)
>$100K * Science: Biology	−1.600*** (0.111)
>$100K * Science: Biology and chemistry	−1.063*** (0.108)
>$100K * Science: Biology, chemistry, and physics	−0.273** (0.110)
>$100K * Science: Other 3 yr combinations	−0.469*** (0.128)
Constant	16.959*** (0.088)
Observations	453,439
Log likelihood	−1,240,707.00
Akaike inf. crit.	2,481,539.00
Bayesian inf. crit.	2,482,222.00

**p* < 0.1; ***p* < 0.05; ****p* < 0.01.

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