Research Report

2025-02

Predicting STEM Achievement: A Comparative Study of ACT® Scores and High School GPA

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Conclusions

In the present study, we find evidence that high school GPA (HSGPA) and ACT® STEM scores are both independently significant predictors of first year GPA (FYGPA) for STEM majors, with HSGPA generally having a stronger individual effect. The study also found that the interaction between HSGPA and ACT STEM scores enhances predictive accuracy which demonstrates a complex and synergistic relationship. By incorporating demographic variables such as gender, race/ethnicity, and family income, we are able to add nuance to the predictive model, with these factors having a direct effect on FYGPA as well as moderating the relationships between HSGPA and ACT STEM scores with FYGPA. The most comprehensive model examined included achievement and demographic factors and explained the greatest variance in FYGPA, further underscoring the complementary roles of HSGPA and ACT STEM scores in assessing academic readiness.

So What?

The study emphasizes the importance of sustained high performance in high school as well as equitable access to resources for students from diverse backgrounds. The study also highlights the complementary role of HSGPA and ACT STEM scores in predicting FYGPA for STEM majors. This study also reaffirms the importance of rigorous high school preparation. Furthermore, since gender, race/ethnicity, and family income directly influence FYGPA and also moderate the relationship between predictors, this leads us to a need for equity-focused interventions.

Now What?

There are several important implications that we can draw from this study. Firstly, for parents and caregivers, this research helps provide actionable insight into supporting their students' educational journey. It emphasizes the need for sustained academic encouragement and support, as well as aid in seeking out equitable resources, particularly for students from lower-income families. Additionally, post-secondary institutions can use these findings to help refine the admissions process by incorporating both HSGPA and ACT STEM scores. This study also suggests that there would be a benefit to creating targeted supports for traditionally underserved populations, thereby promoting diversity and inclusion within STEM majors.

About the Authors

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Dr. Sanchez is a lead 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 on studying the transition between high school and college and supporting the decision-making capacity of college administrators, students, and their families. 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.

Acknowledgements

The author would like to thank Jeff Allen and Jill McVey for their comments on previous drafts of this report.

Introduction

The usefulness of college admissions test scores and high school GPA for predicting college success, particularly in STEM (science, technology, engineering, and mathematics), has been widely debated. As colleges across the country face challenges in STEM student retention and achievement, understanding the factors that contribute to college success is crucial (Sithole et al, 2017; Cromley et al, 2016). Standardized tests, such as the ACT®, have a long history of being used as indicators of college readiness. Some recent studies suggest that high school GPA (HSGPA) may offer unique or even superior predictive power for academic success (Allensworth & Clark, 2020). However, Walton (2023) found that when college GPA was adjusted for course difficulty, ACT scores had a stronger correlation with college performance, suggesting that ACT scores are a more accurate predictor of academic success than traditional calculations may imply.

Sanchez (2024) highlights that high school GPA (HSGPA) is the most significant predictor of ACT Composite scores, outperforming socioeconomic status, demographics, and school-level characteristics. Using dominance analysis, the study shows that HSGPA consistently predicts ACT scores better than other factors, including family income, race/ethnicity, gender, and advanced coursework. Advanced coursework, particularly in math, also significantly predicts ACT scores, though not as strongly as HSGPA. The findings emphasize the critical role of a rigorous high school curriculum and strong academic performance in preparing students for college readiness, with HSGPA explaining a substantial portion of the variance in ACT scores.

There are many studies that illustrate the importance of the ACT for college success. Miller (2022) found that ACT scores helped identify students prepared for college rigor by examining students' GPA in their third year of college, arguing that these scores reflect students' abilities to understand both basic and complex, content-specific material. Thompson et al. (2018) found that ACT math scores were significant predictors of student success in an introductory biology course. Similarly, Shepherd (2019) demonstrates that ACT scores are significant predictors of college success, particularly in STEM courses, aligning with previous research and highlighting the importance of standardized testing. Ayeni (2022) found that ACT scores, particularly in English and math, significantly predicted STEM GPA, suggesting that higher ACT scores in these subjects are associated with better academic performance in STEM fields.

Chen and Upah (2020) found that ACT scores, in conjunction with academic self-efficacy, first-term credits completed, and academic integration, were significant predictors of retention and program selection among undeclared engineering students. Westrick and Radunzel (2018) found that both HSGPA and ACT Composite scores were strong predictors of success in math-intensive STEM majors. Students with higher ACT math and science scores, along with those who took advanced courses like calculus in high school, were more likely to complete a math-intensive STEM degree within four years.

Radunzel et al. (2016) highlight the role of ACT scores as indicators of academic preparedness for STEM, particularly when combined with other preparation indicators. This study revealed that students with higher ACT scores in math and science, in addition to strong HSGPA and completion of advanced coursework, were more likely to succeed in STEM fields.

The ACT STEM benchmark is a score indicating a student's readiness for college-level STEM courses. It is the minimum ACT score needed to have a high probability (75%) of earning a grade of C or higher in first-year college courses such as calculus, biology, chemistry, and physics. The benchmark score for ACT STEM is 26. This benchmark was determined by identifying the most common first-year STEM courses and determining the ACT math and science scores associated with a 50% probability of earning a grade of B or higher in those courses (Mattern, Radunzel, & Westrick, 2015). Students meeting the benchmarks were more likely to achieve a cumulative GPA of 3.0 or higher, persist in their major, and graduate with a STEM-related degree.

Students enrolled in STEM majors often have foundational courses in mathematics, physics, chemistry, biology, and computer science that they must take during their first year. These courses are prerequisites for upper-level STEM courses. The STEM programs, themselves, may have a fixed curriculum with a sequence of courses requiring students to focus on STEM courses early in their post-secondary career. There is also evidence that STEM majors are more likely to take mathematics, natural sciences, and engineering courses compared to their non-STEM peers (Elrod & Park, 2020). For these reasons, it is important to look at the FYGPA outcomes for STEM majors, specifically.

In the context of these studies, the present study seeks to explore the combined and comparative predictive validity of ACT STEM scores (the average of math and science section scores) and high school GPA on first-year college GPA (FYGPA) for STEM majors. Additionally, this study will explore how demographic factors such as gender, race/ethnicity, and socioeconomic status moderate these relationships. By integrating these predictors, this study aims to contribute to a more effective framework for predicting STEM success in college. This study focuses on two research questions:

1. How well do ACT STEM scores and high school GPA independently and jointly predict FYGPA for STEM majors?

2. Do demographic variables such as gender, race/ethnicity, and family income moderate the relationship between ACT STEM scores, high school GPA, and FYGPA among STEM majors?

Methods

Analytical Sample

The analytical sample consisted of 2,691 students who graduated in the class of 2022 in a southern state, enrolled in a public postsecondary institution immediately after high school, declared a STEM major in college, and took the ACT as part of either school-day testing or on a national test date. Students were required to have valid data for FYGPA, ACT STEM Score, and HSGPA. The sample is further described in the descriptive statistics section below.

Measures

ACT STEM Score. The ACT STEM score is an average of the student's mathematics and science scores. These scores may have been attained either during statewide school-day testing or during a national test administration. For students in the study who took the ACT test more than once, their most recent score as of the July of their year of high school graduation was used.

High School GPA (HSGPA). Students reported their high school grades in up to 23 courses in subjects including English, mathematics, social studies, and natural science. These grades were averaged to determine a cumulative HSGPA on a scale of 0 to 4.0. Prior research has demonstrated a strong correlation between students self-reported HSGPA and their transcript GPA (Sanchez & Buddin, 2016). Additional research has supported the use of self-reported grades as a reliable substitute for transcript reported grades in research contexts (Camara et al., 2003; Kuncel et al., 2005; Shaw & Mattern, 2009).

Demographic Characteristics. As part of the ACT registration process, students reported demographic information. This study made use of race/ethnicity, family income, and gender. Gender included categories of male, female, another gender, prefer not to respond, and no response provided. For analysis purposes, students who responded with another gender (0.1%), preferred not to respond (0.4%), or did not provide a response (5.1%) were omitted due to small group sample sizes. Race/ethnicity groups included African American, American Indian/Alaska native, Asian, Hispanic, white, two or more races, prefer not to respond, or did not provide a response. There were three Native Hawaiian/Pacific Islander students in the sample that were omitted due to sample size. For analysis purposes, students who responded as American Indian/Alaska native (0.4%) were combined with students who responded as having two or more races (4.7%). Family income was categorized as less than $36,000, $36,000–$60,000, $60,000–$100,000, greater than $100,000, and not reporting family income.

First-year GPA (FYGPA). FYGPA was obtained from student course grade records obtained from the colleges where students enrolled immediately after high school.

STEM Major Declaration. Student-declared major was obtained from students' transcripts at the colleges where they enrolled immediately after high school. A major was classified as a STEM major if it was included in the official STEM Major Classification of Instruction Program (CIP) codes defined by the state's department of higher education.

Data Analysis

To evaluate the research questions, six hierarchical linear models were estimated accounting for the college the student attended. The six models include:

1. FYGPA ~ ACT STEM score
2. FYGPA ~ HSGPA

3. FYGPA ~ ACT STEM score + HSGPA + HSGPA * ACT STEM score

4. FYGPA ~ HSGPA + HSGPA * Gender + HSGPA * Race/ethnicity + HSGPA * Family Income

5. FYGPA ~ ACT STEM score + ACT STEM score * Gender + ACT STEM score * Race/ethnicity + ACT STEM score * Family Income

6. FYGPA ~ ACT STEM score + HSGPA + Family Income + Gender + Race/ethnicity + HSGPA*ACT STEM score + ACT STEM score * Gender + HSGPA*Gender + HSGPA*Race/ethnicity

In Models 1 and 2, the effect of predicting FYGPA by using only ACT STEM score and HSGPA, respectively, were examined. In Model 3, both academic achievement indicators were included, as well as the interaction between them. In Models 4 and 5, the interactions between HSGPA and ACT STEM score with demographics were examined in separate models. Model 6 included both academic achievement indicators as well as selected interaction terms between ACT STEM score and race/ethnicity, as well as the HSGPA interaction with gender and race/ethnicity. To evaluate multicollinearity in this model, I estimated a fixed effects model and utilized variance inflation factor statistics to exclude interactions with multicollinearity concerns. All continuous variables were standardized to have a mean of 0 and a standard deviation of 1.

Among these six models, certain models are nested under other more complex models. For example, Model 1 is nested within Models 3, 5, and 6; Model 2 is nested within Models 3, 4, and 6; and Model 3 is nested within Model 6.

Results

Descriptive Statistics

Table 1 shows that, of the 7,319 students in the sample, approximately 61% were female, 67% were white, and 30% came from families with an income of over $100,000.

Table 1. Sample Demographics

Characteristic		*N* (%)
n		7,319 (100%)
Gender	Female	4,444 (60.7)
	Male	2,873 (39.3)
Race/ethnicity	African American	847 (11.6)
	American Indian/Alaskan Native	30 (0.4)
	Asian	205 (2.8)
	Hispanic	878 (12.0)
	White	4,923 (67.3)
	Prefer not to respond/Missing	99 (1.4)
	Two or more races	334 (4.6)
Family Income	< $36K	1,816 (24.8)
	$36K–$60K	1,461 (20.0)
	$60K–$100K	1,880 (25.7)
	> $100K	2,159 (29.5)

Table 2 displays summary statistics for HSGPA, ACT STEM scores, and FYGPA. Table 3 shows that there is a moderately strong correlation between HSGPA and FYGPA, a moderate correlation between ACT STEM scores and FYGPA, and a moderate correlation between HSGPA and ACT STEM scores. Figures 1–3 display histograms for HSGPA, ACT STEM scores, and FYGPA. In these figures, both HSGPA and FYGPA are highly skewed, with most students scoring towards the upper end of their scale near 4.0. ACT STEM scores, on the other hand, are only slightly skewed.

Table 2. Sample Achievement

Achievement	Mean (*SD*)
HSGPA	3.55 (0.44)
ACT Stem Score	21.01 (4.56)
FYGPA	3.00 (0.90)

Table 3. Achievement Correlation Matrix

—	FYGPA	HSGPA	ACT STEM
FYGPA	1.00	—	—
HSGPA	0.51	1.00	—
ACT STEM	0.36	0.48	1.00

Figure 1. Histogram of Sample HSGPA

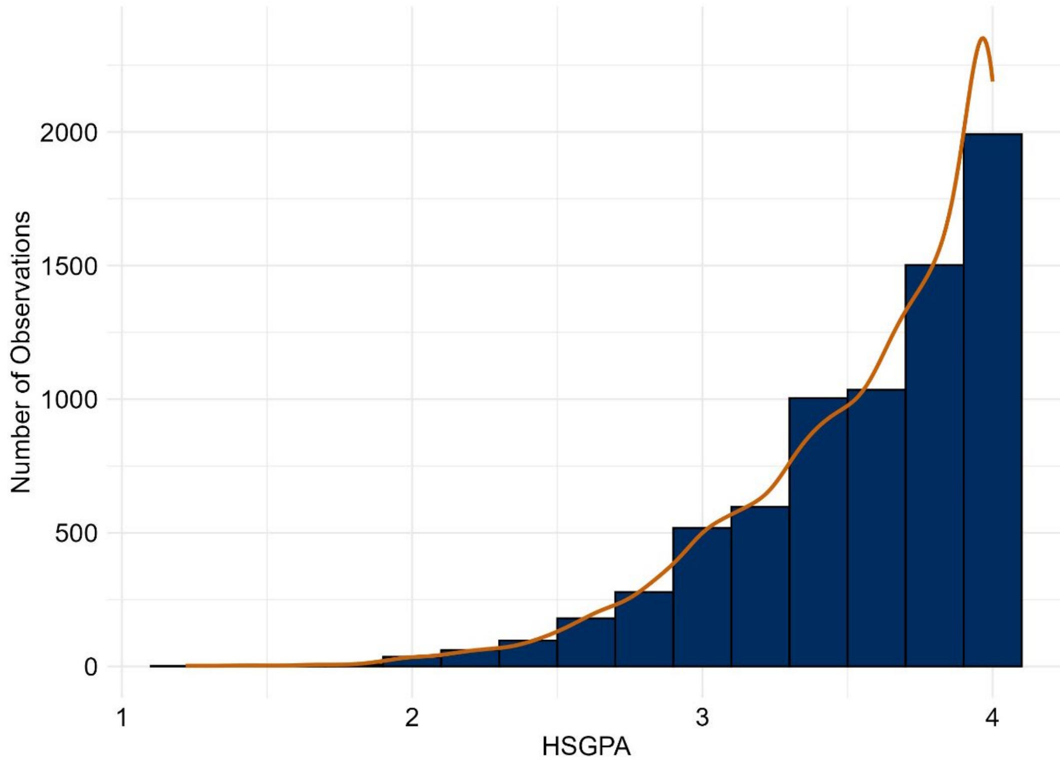


Figure 2. Histogram of Sample ACT STEM Score

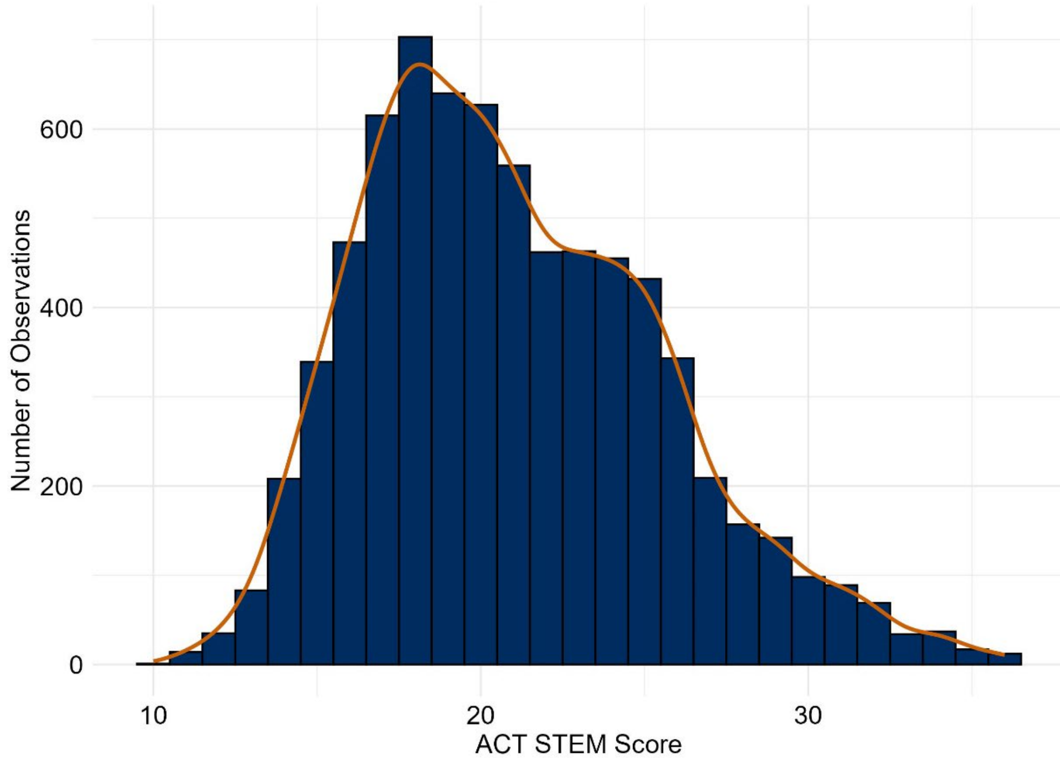
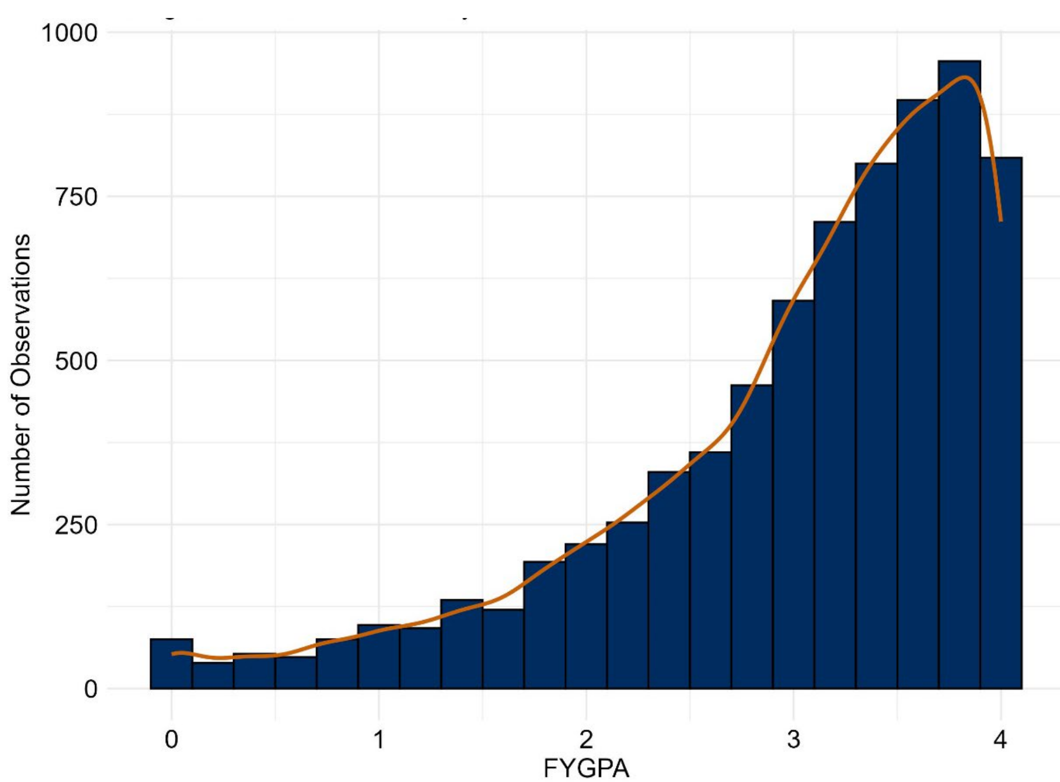


Figure 3. Histogram of Sample FYGPA



Hierarchical Linear Modeling Results

To evaluate the significance of each predictor and interaction term in the six hierarchical linear models (HLMs), I conducted a Wald test using Type III sum of squares. This test evaluates whether the inclusion of each predictor or interaction significantly improves the model's ability to predict FYGPA. This Wald test was appropriate as it allowed an evaluation of each variable's effect, accounting for the random intercept at the college level. Results of the Wald tests are presented in Table 4, where *p*-values indicate the significance of each predictor and interaction term.

As Table 4 shows, in Models 1 and 2 both HSGPA and ACT STEM scores were significant predictors of FYGPA. Model 3 shows that, in addition to the significant main effects for these two achievement indicators, the interaction was also significant. In Model 4, the addition of demographic variables and relevant interactions shows there is a significant main effect for gender, race/ethnicity, and family income, in addition to a significant interaction effect between HSGPA and gender. In Model 5, for ACT STEM scores, the addition of demographic variables resulted in significant main effects for gender, race/ethnicity, family income, and the ACT STEM scores interactions with gender and race/ethnicity. In Model 6, which included both academic achievement indicators as well as demographics and selected interaction terms, 1) both achievement indicators displayed a significant main effect; 2) gender, race/ethnicity, and income displayed a significant main effect; 3) the interaction between HSGPA and ACT STEM scores was significant; 4) the interactions between HSGPA and gender as well as race/ethnicity were significant; and 5) the interaction between ACT STEM scores with ethnicity was not significant. The full model standardized coefficients and relevant statistics are provided in the appendix.

Table 4. Model Predictor Significance

Predictor	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
HSGPA	<0.001	—	<0.001	<0.001	—	<0.001
ACT STEM	—	<0.001	<0.001	—	<0.001	<0.001
HSGPA*ACT STEM	—	—	<0.001	—	—	<0.001
Gender	—	—	—	<0.001	<0.001	<0.001
Ethnicity	—	—	—	<0.001	<0.001	<0.001
Family Income	—	—	—	<0.001	<0.001	<0.001
HSGPA*Gender	—	—	—	0.000	—	<0.001
HSGPA*Ethnicity	—	—	—	0.062	—	0.011
HSGPA* Family Income	—	—	—	0.137	—	—
ACT STEM*Gender	—	—	—	—	0.006	0.804
ACT STEM*Ethnicity	—	—	—	—	0.001	—
ACT STEM* Family Income	—	—	—	—	0.617	—

Note. p-values are rounded to the thousands decimal place.

In this analysis, I used a series of hierarchical linear models to predict FYGPA, including a random intercept to account for variation between colleges. One of the goals of this approach was to determine which combination of predictors provides the best model fit by comparing models with increasingly complex predictor sets using Likelihood Ratio Tests (LRT) based on maximum likelihood estimation. Specifically, I start with Model 1 and 2 that include individual predictors, and subsequently add interactions in Model 3. Demographics are added in Models 4 and 5, and finally the full model, Model 6, includes both achievement indicators, demographics, and relevant interactions.

First, I compared Model 1 with Model 3, that is, I compared a model with only ACT STEM scores with a model that includes the addition of high school GPA and an interaction between ACT STEM scores and HSGPA. The LRT results showed that Model 3 demonstrated significantly better fit than Model 1 ($\chi^2 = 1{,}373.7$; $df = 2$; $p < 0.001$), which indicates that adding high school GPA and its interaction with ACT STEM scores provides a substantially better fit. Next, I compared Model 2, that included only HSGPA, with Model 3. Once again, Model 3 demonstrated significantly better fit ($\chi^2 = 248.78$; $df = 2$; $p < 0.001$), highlighting the value of including both academic predictors and their interaction in predicting FYGPA.

LRTs between Model 4 and Model 6 as well as between Model 5 and Model 6 could not be conducted because each pair of model comparisons contained the same number of parameters and 0 degrees of freedom.

Finally, a comparison between Model 3 and Model 6 examines whether adding demographic interactions further improves model fit, as it includes demographics as well as interaction terms between HSGPA and ACT STEM scores with key demographic variables. The LRT results show that Model 6 demonstrated better fit ($\chi^2 = 204.97$; $df = 16$; $p < 0.001$), which suggests that incorporating demographic interactions significantly enhanced the model's predictive ability.

These LRT tests demonstrated that both academic achievement factors, HSGPA and ACT STEM scores, as well as demographic characteristics, meaningfully contribute to the prediction of FYGPA. The final model, Model 6, which includes academic achievement predictors, demographic variables, and interaction terms, provides the best fit among all six models examined.

Table 5 presents the correlation between observed and predicted FYGPA and the explanatory power of the six different models. The correlation coefficient (r_{xy}) serves to provide a practical measure of the relationship between the observed and predicted FYGPA values for each model. This represents how well each model predicts FYGPA. The marginal R-squared (R^2) statistic represents the proportion of variance explained in FYGPA by the fixed effects included in each model. Specifically, it examines the contribution of the predictors explicitly included in the model while not considering random institution effects. The conditional R^2, on the other hand, represents the proportion of variance in FYGPA that is explained by both the fixed and random effects. This is a more comprehensive measure of the model's explanatory power as it includes random institution effects. When considered together, marginal and conditional R^2 helps us to understand the relative importance of the fixed effects in comparison to the total variance explained. For example, if there is a large difference between the marginal and conditional R^2, this would indicate that the institution effects contribute significantly to the outcome. On the other hand, if there are smaller differences between the marginal and conditional R^2 this suggests that most of the variance is explained by the fixed effects rather than the institution effects.

Table 5. Percentage of Variance Explained by Each Model

Model	r_{xy}	Marginal R^2	Conditional R^2
Model 1	0.39	13%	16%
Model 2	0.52	26%	27%
Model 3	0.54	29%	31%
Model 4	0.54	29%	30%
Model 5	0.44	19%	22%
Model 6	0.56	32%	34%

As shown in Table 5, correlation coefficients tended to increase with additional model complexity. This demonstrates the improved predictive accuracy of more comprehensive models. For example, the correlation for Model 1 was 0.39 which is a modest correlation between predicted and observed FYGPA. In comparison, Model 6 achieves the highest correlation at 0.56 which reflects a much stronger relationship. This improvement underscores why it is important to consider factors such as HSGPA, ACT scores, demographic factors, as well as their interactions when explaining student performance. The trends observed in these correlation coefficients across models demonstrates the practical benefits of using more complex models to improve predictive accuracy. These findings serve to compliment the variance explained measures provided by the marginal and conditional R^2.

Model 1 includes only the ACT STEM scores and the institution effect, explaining a modest portion of the fixed and total effects variance in FYGPA. Model 2 uses high school GPA (HSGPA) and the institution effect, explaining more of the fixed and total effects variance than Model 1. Model 3 combines ACT STEM scores and HSGPA, the interaction between ACT STEM scores and HSGPA, and the institution effect, resulting in a higher explanatory power than the first two models.

Model 4 incorporates HSGPA and its interactions with gender, race/ethnicity, and family income, along with the institution effect, explaining a similar amount of the fixed and total effects variance as Model 3. Model 5 includes ACT STEM score and its interactions with gender, race/ethnicity, and family income, plus the institution effect, explaining more of the fixed and total effects variance than Model 1 but less than Model 1, Model 3, and Model 4. Finally, Model 6 is the most comprehensive, including ACT STEM score, HSGPA, family income, gender, race/ethnicity, and various interactions, along with the institution effect. This model explains the most fixed and total effects variance in FYGPA, indicating that a combination of academic performance, demographic factors, and their interactions provides the most robust explanation of variance in FYGPA.

In all models, the Marginal and Conditional R^2 values are similar. This suggests that, in this set of models, most of the variance is explained by the academic and demographic variables included in the models.

How well do ACT STEM scores and high school GPA independently and jointly predict first-year college GPA for STEM majors?

Model fit was assessed using R^2 while regression coefficients are provided to give insight into the individual effects of the predictors. In Model 1, which included only ACT STEM scores, the fixed-effects R^2 was 0.133, indicating that 13.3% of the fixed effects variance in FYGPA was explained by ACT STEM scores alone. In Model 2, where only HSGPA was used to predict FYGPA, the fixed effects R^2 was 0.259, suggesting that HSGPA explained 25.9% of the fixed effects variance in FYGPA, a notably higher percentage of explained variance than Model 1.

Model 3, which included both ACT STEM scores as well as HSGPA to predict FYGPA, had a fixed effects R^2 of 0.293, the highest of these three models suggesting a combined predictive effect. The inclusion of both achievement indicators along with their interaction explains 29.3% of the fixed effects variance in FYGPA. The standardized coefficient for ACT STEM scores dropped to 0.14 when combined with HSGPA, compared to the 0.34 in the single predictor model, which suggests that much of ACT STEM score's effect was shared with or moderated by HSGPA. Conversely, HSGPA maintained a high standardized coefficient of 0.44 in the combined model, similar to its predictive power in Model 2.

It is worth noting that the interaction term between ACT STEM score and HSGPA in Model 3 had a standardized coefficient of 0.07, indicating a statistically significant joint contribution to FYGPA. This interaction suggests that the predictive power of ACT STEM scores on FYGPA may be enhanced when combined with higher values of HSGPA, which captures a nuanced relationship between these two predictors. Therefore, while both ACT STEM scores and HSGPA independently contribute to predicting FYGPA, their combined and interactive effects offer a more comprehensive model with improved predictive accuracy.

Examining table A2, Model 4 (the model including HSGPA and demographic variables) resulted in a fixed effects R^2 of 0.285. HSGPA remained a strong significant predictor with a coefficient of 0.37, suggesting that HSGPA remains a strong predictor when demographic factors are considered. The model with ACT STEM scores and demographics, Model 5, had a lower fixed effects R^2 value of 0.190 compared to the HSGPA model (Model 4). This suggests that a model which includes only HSGPA and demographics has stronger predictive power than a model which contains only ACT STEM scores and demographics.

In the full model, Model 6, which includes HSGPA, ACT STEM scores, and demographic variables, the fixed effects R^2 was 0.317, which was the highest value among all models. In this model, HSGPA remained the strongest predictor with a coefficient of 0.35 while ACT STEM scores had a lower coefficient of 0.13. This suggests that even in the most comprehensive model, HSGPA has a stronger independent effect on FYGPA than ACT STEM scores. The significant interaction between HSGPA and ACT STEM scores suggests that the effect of ACT

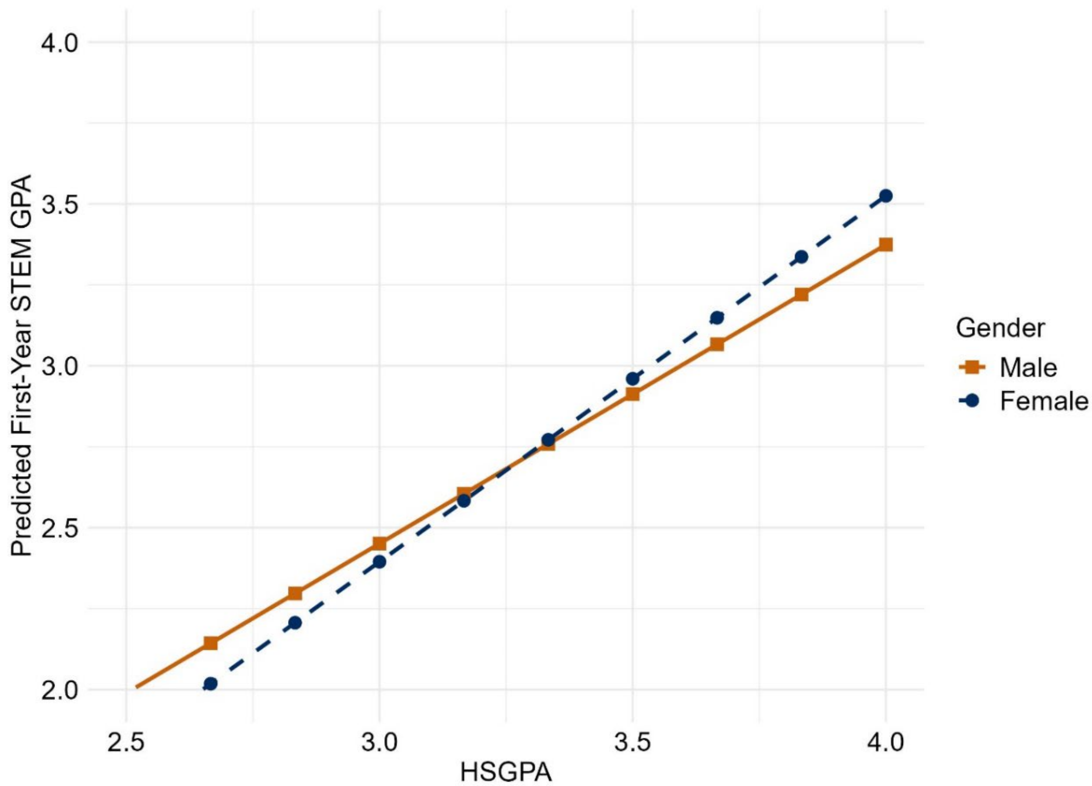
STEM scores on prediction of FYGPA scores would be higher for students who have a high HSGPA. This indicates that when these two are used together and allowed to covary, the predictive power on FYGPA is greater than in a model with each predictor individually. Collectively, Models 3 and 6 demonstrate that using both achievement indicators in a model together provides better predictive power than using either alone.

Do demographic variables such as gender, race/ethnicity, and family income moderate the relationship between ACT STEM scores, high school GPA, and FYGPA among STEM majors?

To answer this question, I will focus on Models 4, 5, and 6 (refer to Tables A2–A4 in the appendix), focusing on the interaction terms between demographic variables and the primary achievement indicators of ACT STEM scores and HSGPA. These interactions will help to determine if demographic factors impact the strength or direction of the relationship between ACT STEM scores, HSGPA, and FYGPA.

In Model 4, Table A2, HSGPA interacts with gender. The interaction between HSGPA and gender, is positive and significant (0.09), indicating that the effect of HSGPA on FYGPA is stronger for female students (Figure 4). This means that, for female students, a one-standard deviation increase in HSGPA corresponds to a greater increase in FYGPA compared to students in the male reference group. This significant interaction suggest that gender moderates the relationship between HSGPA and FYGPA, with female students showing a stronger relationship between HSGPA and FYGPA.

Figure 4. Predicted FYGPA Based on HSGPA, by Gender



Model 5 reveals two significant interactions between ACT STEM scores and demographic factors, which indicates how the predictive strength of ACT STEM scores on FYGPA varies by demographic group. For example, the interaction term for ACT STEM scores and gender, is positive and significant (0.06, Figure 5), indicating that the relationship is stronger for female students. A positive and significant interaction between ACT STEM scores and African American race/ethnicity, 0.13, implies that the relationship between ACT STEM scores and FYGPA is stronger for African American students compared to white students (Figure 6). This indicates that within this group, higher ACT STEM scores are associated with larger gains in FYGPA compared to white students. Additionally, the positive interaction observed between ACT STEM scores and the group of students who preferred not to disclose or did not provide their racial/ethnic information suggests that ACT STEM scores have a stronger predictive effect on FYGPA, similar to the pattern observed with African American students.

Figure 5. Predicted FYGPA Based on the ACT STEM Score, by Gender

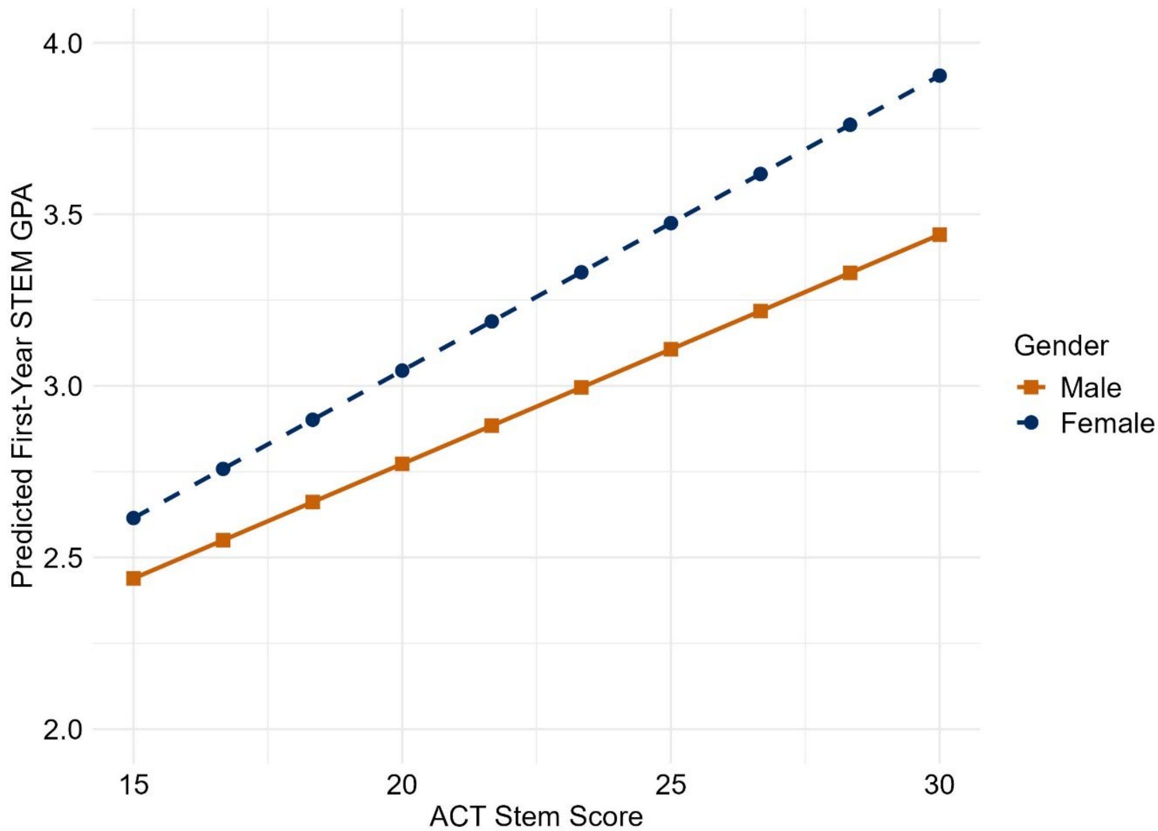
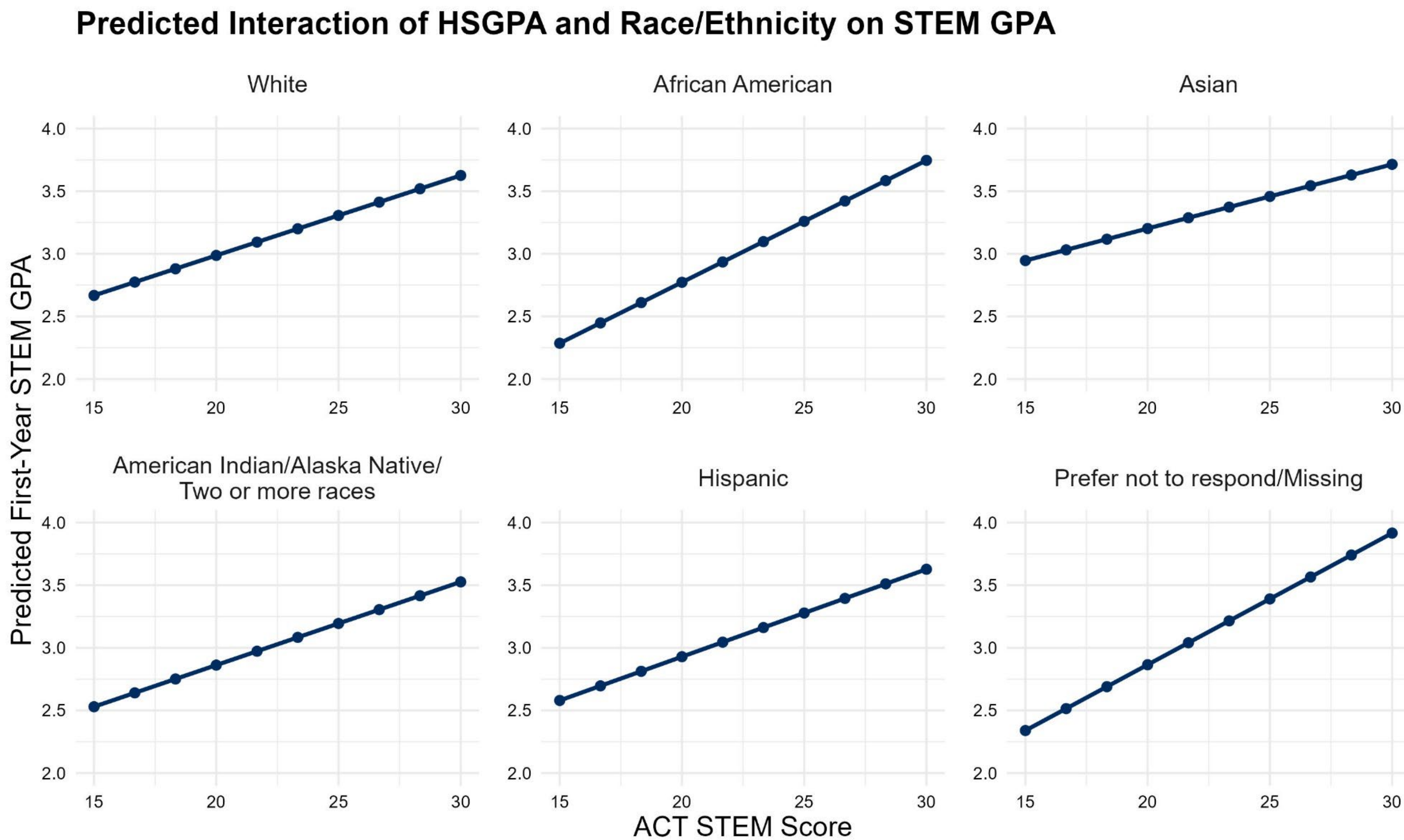


Figure 6. Predicted FYGPA Based on the ACT STEM Score, by Race/Ethnicity



In Model 6, the full model (Table A4), we have a more comprehensive perspective of the demographics' interaction with ACT STEM scores and HSGPA. Recall that in this model, due to multicollinearity concerns, interactions between the demographic variables and achievement indicators (i.e., ACT STEM and HSGPA) were limited to the HSGPA interactions with both gender and race/ethnicity, and the ACT STEM score interaction with gender. Among these interactions, the interaction between ACT STEM scores and gender was not significant. When examining the interaction between HSGPA and gender, the interaction is positive and significant, 0.11, which once again tells us that female students have a stronger relationship between HSGPA and FYGPA than male students (Figure 7). The interaction between HSGPA and race/ethnicity, specifically for students who preferred not to provide their race/ethnicity or did not provide their race/ethnicity, was positive and significant, which indicates that an increase in HSGPA resulted in a steeper increase in FYGPA for these students compared to white students (Figure 8). As the interaction between ACT STEM scores and gender was not significant, it is not plotted here.

Figure 7. Predicted FYGPA Based on the HSGPA Model, by Gender

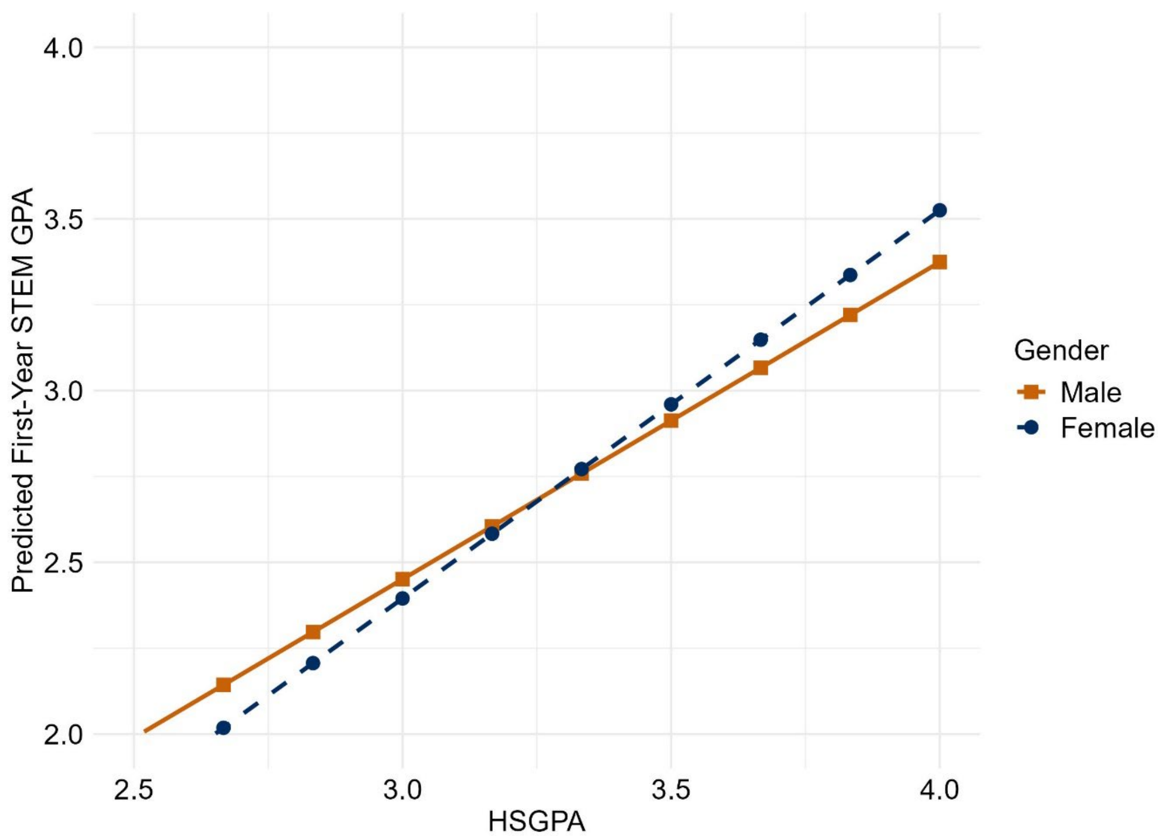
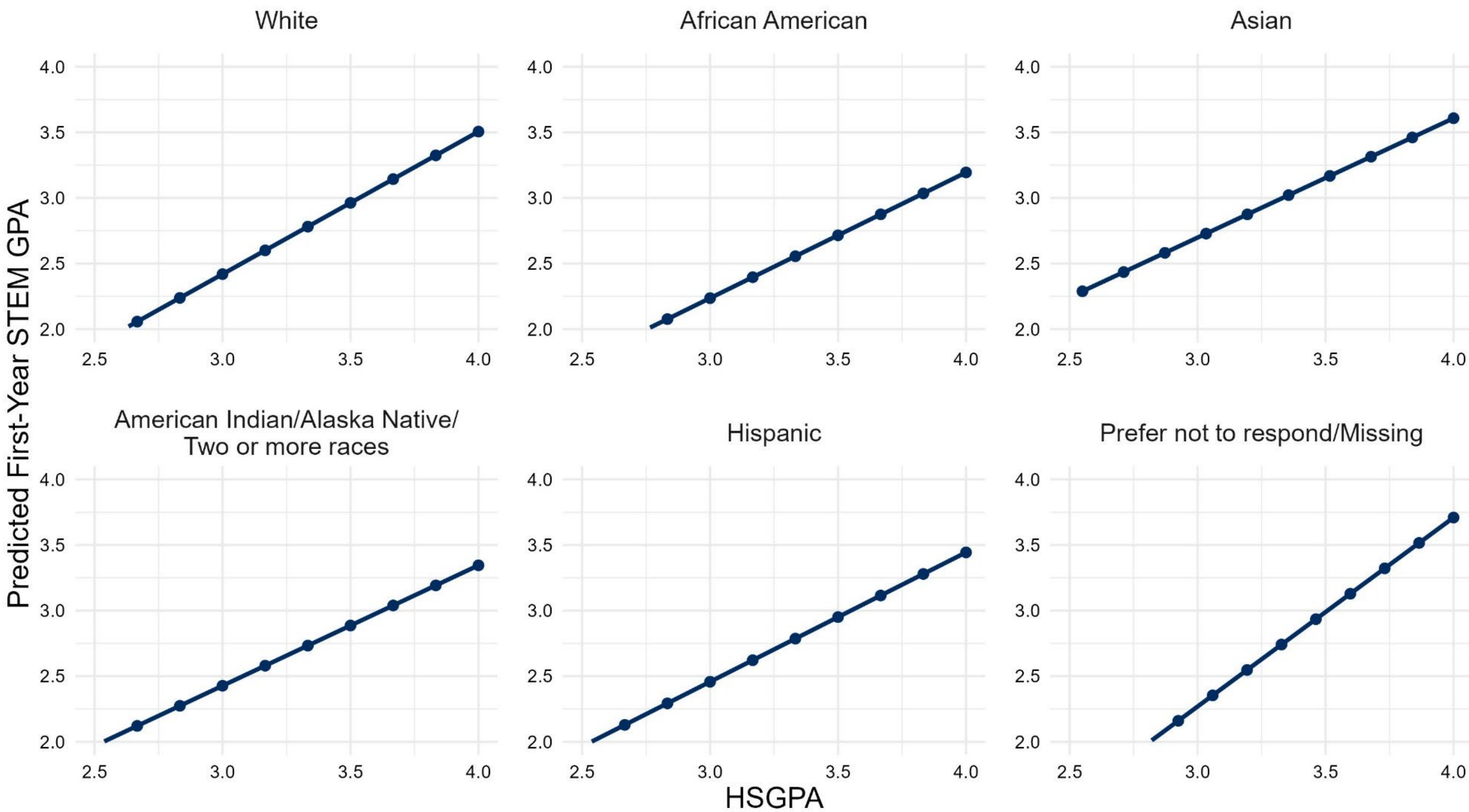


Figure 8. Predicted FYGPA Based on the HSGPA Model by Race/Ethnicity



Discussion

The HLM analysis presented in this paper provides insight into the relationship between HSGPA and ACT STEM scores as predictors of FYGPA for STEM majors, emphasizing the importance of academic and demographic predictors. The results demonstrate that both HSGPA and ACT STEM scores are independently significant predictors of FYGPA, with HSGPA showing a stronger individual effect. When used in conjunction with each other, these academic indicators, particularly through their interaction, result in a predictive model with greater predictive accuracy, showing that the relationship between these predictors is both complex and synergistic.

The incorporation of demographic variables such as gender, race/ethnicity, and family income added additional nuance to the findings. These factors appear to have direct effects on FYGPA, but also, in the case of gender and race/ethnicity, moderated the relationships between HSGPA, ACT STEM scores, and FYGPA.

Examining the final model, which included all achievement predictors and demographic variables, I found that this model explained the most amount of variance in FYGPA. This model confirms the important relationship between ACT STEM scores and HSGPA with FYGPA. The findings of this study demonstrate that while both HSGPA and ACT STEM scores are useful for predicting FYGPA, they provide complimentary information.

This study highlights the importance of sustained effort and high achievement, as both HSGPA and ACT STEM scores are important predictors of FYGPA among STEM majors. The strong relationship between HSGPA and FYGPA for STEM majors indicated the importance of consistently high performance in high school. The study also illustrates how ACT STEM scores can have a complementary effect with HSGPA, as each provided unique insight into students' academic readiness for STEM majors.

For parents or other caregivers, these findings offer valuable guidance in supporting their student's academic journey into STEM majors. Caregivers should be aware of the importance of sustained support for their child's educational endeavors. Caregivers of traditionally underserved populations can use this information to advocate for their children's equitable access to educational resources and access to other community resources that can help bolster their child's achievement.

For postsecondary institutions, these findings highlight the importance of considering both HSGPA and ACT STEM scores when assessing the likelihood of success of students interested in STEM majors. Moreover, the findings serve to underscore the need for targeted support for traditionally underserved populations. With this information in hand, custom support plans can be developed for students who declare a STEM major.

Limitations

The present study is limited to a single year's graduating class who lived in a state with a state-wide adoption contract with ACT, enrolled immediately after high school in a public postsecondary institution, and declared a STEM major. The findings of this study should be interpreted within the context of students who enrolled immediately after high school in a public postsecondary institution, identified as male or female, and declared a STEM major. Moreover, this study did not account for the specific college courses students took in their first year or the courses' difficulty. Incorporation of this information would likely strengthen the prediction of FYGPA. The restriction to students from a one state may limit the generalizability of these findings. Additionally, the present study relied on self-reported HSGPA. While, as noted, prior research has demonstrated the appropriateness of using self-reported HSGPA for research purposes, it remains possible that some self-report bias remains in the responses.

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Appendix

Table A1. Standardized Coefficients for Achievement Models Predicting FYGPA (Model 1, 2, & 3)

Predictors	ACT STEM Model (Model 1)	HSGPA Model (Model 2)	ACT STEM & HSGPA Model (Model 3)
(Intercept)	3.02 ***	3.01 ***	3.01 ***
ACT STEM	0.34 ***	—	0.14 ***
HSGPA	—	0.47 ***	0.44 ***
HSGPA * ACT STEM	—	—	0.07 ***
σ^2	0.69	0.60	0.58
τ_{00}	0.02	0.01	0.01
ICC	0.03	0.01	0.02
$N_{Colleges}$	31	31	31
Observations	7,316	7,316	7,316
Marginal R^2 / Conditional R^2	0.133 / 0.157	0.259 / 0.269	0.294 / 0.308

Note. *p < 0.05; **p < 0.01; ***p < 0.001. The lmer package in *R* could not calculate an intraclass correlation coefficient (ICC) for Model 2. This is likely due to the very low between-groups variance shown in the data.

Table A2. Standardized Coefficients for HSGPA Model Predicting FYGPA (Model 4)

Predictors	Estimates
(Intercept)	2.87 ***
HSGPA	0.37 ***
Gender: Female	0.08 ***
Race/Ethnicity: African American	−0.26 ***
Race/Ethnicity: Asian	0.23 ***
Race/Ethnicity: Combined Group	−0.07
Race/Ethnicity: Hispanic	0.04
Race/Ethnicity: Prefer not to respond/Missing	0.07
FAMILY INCOME: $36K–$60K	0.13 ***
FAMILY INCOME: $60K–$100K	0.15 ***
FAMILY INCOME: > $100K	0.19 ***
HSGPA * Gender: Female	0.09 ***
HSGPA * Race/Ethnicity: African American	−0.03
HSGPA * Race/Ethnicity: Asian	−0.03
HSGPA * Race/Ethnicity: Combined Group	−0.06
HSGPA * Race/Ethnicity: Hispanic	−0.03
HSGPA * Race/Ethnicity: Prefer not to respond/Missing	0.17 *
HSGPA * FAMILY INCOME: $36K–$60K	0.02
HSGPA * FAMILY INCOME: $60K–$100K	0.03
HSGPA * FAMILY INCOME: >$100K	0.06 *
σ^2	0.58
$\tau_{00\ COLLEGE\_CODE}$	0.01
ICC	0.02
$N_{Colleges}$	31
Observations	7,316
Marginal R^2 / Conditional R^2	0.285 / 0.302

Note. *p < 0.05; **p < 0.01; ***p < 0.001.

Table A3. Standardized Coefficients for ACT STEM Model Predicting FYGPA (Model 5)

Predictors	Estimates
(Intercept)	2.77 ***
ACT STEM	0.31 ***
Gender: Female	0.30 ***
Race/Ethnicity: African American	−0.18 ***
Race/Ethnicity: Asian	0.29 ***
Race/Ethnicity: Combined Group	−0.11 *
Race/Ethnicity: Hispanic	0.04
Race/Ethnicity: Prefer not to respond/Missing	−0.06
Family Income: $36K–$60K	0.12 ***
Family Income: $60K–$100K	0.16 ***
Family Income: > $100K	0.21 ***
ACT STEM * Gender: Female	0.05 **
ACT STEM * Race/Ethnicity: African American	0.13 **
ACT STEM * Race/Ethnicity: Asian	−0.11 *
ACT STEM * Race/Ethnicity: Combined Group	0.04
ACT STEM * Race/Ethnicity: Hispanic	0.02
ACT STEM * Race/Ethnicity: Prefer not to respond/Missing	0.17 *
ACT STEM * Family Income: $36K–$60K	−0.02
ACT STEM * Family Income: $60K–$100K	−0.04
ACT STEM * Family Income: > $100K	−0.04
σ^2	0.66
τ_{00}	0.02
ICC	0.04
N	31
Observations	7,316
Marginal R^2 / Conditional R^2	0.190 / 0.219

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

Table A4. Standardized Coefficients for ACT STEM & HSGPA Model Predicting FYGPA (Model 6)

Predictors	Estimates
(Intercept)	2.84 ***
HSGPA	0.35 ***
ACT STEM	0.13 ***
Gender: Female	0.14 ***
Race/Ethnicity: African American	−0.18 ***
Race/Ethnicity: Asian	0.22 ***
Race/Ethnicity: Combined Group	−0.07
Race/Ethnicity: Hispanic	0.06 *
Race/Ethnicity: Prefer not to respond/Missing	0.06
Family Income: $36K–$60K	0.12 ***
Family Income: $60K–$100K	0.13 ***
Family Income: > $100K	0.16 ***
HSGPA * ACT STEM	0.08 ***
ACT STEM * Gender: Female	−0.01
HSGPA * Gender: Female	0.11 ***
HSGPA * Race/Ethnicity: African American	0.04
HSGPA * Race/Ethnicity: Asian	−0.10
HSGPA * Race/Ethnicity: Combined Group	−0.06
HSGPA * Race/Ethnicity: Hispanic	−0.02
HSGPA * Race/Ethnicity: Native Hawaiian/Pacific Islander	0.08
HSGPA * Race/Ethnicity: Prefer not to respond/Missing	0.18 **
σ^2	0.56
τ_{00}	0.02
ICC	0.03
$N_{Colleges}$	31
Observations	7,316
Marginal R^2 / Conditional R^2	0.317 / 0.337

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

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