Research Report

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Has the Predictive Validity of High School GPA and ACT Scores on Postsecondary Enrollment Changed Over Time?

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ACT®

Conclusions

Accounting for student characteristics and school effects, using both high school GPA (HSGPA) and ACT Composite score was more predictive of postsecondary enrollment than using either predictor alone. When used together, the predictive power of HSGPA increased from 2010 to 2021, while the predictive power of the ACT Composite score decreased during this period. HSGPA had greater predictive power than did the ACT Composite score after 2014. We believe the adoption of test-optional admissions policies before and especially after the COVID-19 pandemic helps explain the increase in predictive power for HSGPA.

So What?

Given the extensive evidence that HSGPA inflation has increased dramatically in recent years, the predictive power of HSGPA alone is threatened. This can result in underprepared students entering postsecondary education and experiencing less favorable outcomes such as higher drop-out rates and higher student loan debt. Combining ACT scores with HSGPA helps provide a more comprehensive picture of which students are prepared to enroll in postsecondary education. This can help postsecondary institutions more accurately predict which students may continue their education after high school.

Now What?

Given the potential threat to the predictive power of HSGPA posed by grade inflation, using ACT scores can help offset the uncertainty of the interpretation of HSGPA and help differentiate between students with the same HSGPA (e.g., students who all have a 4.0 HSGPA). HSGPA and ACT scores measure different aspects of student achievement; therefore, they provide complementary information. We recommend using both HSGPA and ACT scores to predict postsecondary enrollment because using both yields the strongest predictive power.

About the Authors

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Xiuhan Chen is a Ph.D. student at the University of Missouri studying Statistics, Measurement, and Evaluation in Education. Her research focuses on the combination of causality and psychometrics. Throughout her academic journey, Ms. Chen has aimed to deepen the understanding of the causal relationship between human behaviors and personality traits.

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Introduction

Grades are among the most important indicators of students' academic success, skill, and knowledge. Not only do grades influence academic awards, academic intervention, and advanced course placement (Feldman, 2018), they also affect athletic or extracurricular eligibility, employment, driving permits, car insurance rates, college admission, scholarships, and financial aid (Griffin & Townsley, 2021). In American high schools, high school grade point average (HSGPA) is one quantitative measure of grades (ACT, 2005). HSGPA is often compared with standardized test scores (such as ACT® test scores). Both ACT scores and HSGPA are common measures of high school students' academic achievement. These measures are typically used to predict students' academic performance or future success, such as first-semester college GPA, first-year college GPA, and college completion. However, HSGPA may not always be an accurate measure of a student's true ability (ACT, 2005). The presence of grade inflation raises questions about the extent to which we should rely on grades to measure of academic achievement or predict future success.

Grade inflation refers to an increase in grades without a concurrent increase in students' true ability or other objective measures of academic performance (Bejar & Blew, 1981; Camara et al., 2004; Gershenson, 2018; Godfrey, 2011). In other words, students' grades may not reflect their true level of content mastery (Chowdhury, 2018). The evidence of grade inflation has been well documented, with research consistently demonstrating that HSGPA has steadily increased over the past several decades, while standardized assessment scores have remained unchanged or declined (ACT, 2005; Bejar & Blew, 1981; Camara et al., 2004; Gershenson, 2020; Godfrey, 2011; Ziomek & Svec, 1995). For example, Ziomek and Svec (1995) chose a sample of 530,000 students from 5,136 public schools between the 1989–1990 and the 1993–1994 school years to demonstrate that there was a steady increase in HSGPA while ACT scores remained constant. A more recent study found that from 2009 to 2019 alone, HSGPA, as reported on a 0.0 to 4.0 scale, increased from 3.00 to 3.11, while National Assessment of Educational Progress (NAEP) scores remained constant (U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics [NCES], National Assessment of Educational Progress [NAEP], 2022a). A second recent study found that from 2010 to 2021, HSGPA among ACT-tested students increased from 3.17 to 3.36 (Sanchez and Moore, 2022).

Detecting grade inflation is challenging, as it requires both grades across time and a stable measure against which to compare them (ACT, 2005; Bejar & Blew, 1981). Finefter-Rosenbluh and Levinson (2015) summarized three approaches to assessing grade inflation. First, grade inflation can be understood by comparing high school grades to standardized test scores using longitudinal data. In the past, HSGPA has been compared to scores from several standardized tests, such as ACT scores (ACT, 2005; Bellott, 1981; Woodruff & Ziomek, 2004; Zhang & Sanchez, 2013), SAT scores (Bejar & Blew, 1981; Godfrey, 2011), NAEP data (U.S. Department of Education, NCES, NAEP, 2020a), and end-of-course exams (Gershenson, 2018). Second, grade inflation can be understood as grade compression. For example, Hurwitz & Lee (2018) used nationally representative data to estimate grade inflation among all high school students who took the SAT. They found that the percentage of students with A averages increased from 38.9% to 47.0% between 1998 and 2016. Meanwhile, there was a 4.2 percentage point decrease in the percentage of students with B averages, followed by a 3.8 percentage point decrease in the percentage of students with C averages. Similarly, Sanchez and Moore (2022) found a decrease in the percentage of students reporting a B average HSGPA from 2010 to 2021 (46.8% and 36.2%, respectively) and an increase in the percentage of students reporting an A average HSGPA from 2010 to 2021 (40.3% and 54.9%, respectively).[1] Lastly, grade inflation can be detected by comparing grades among high schools. Nord (2011) recorded that grade inflation was concentrated in wealthier and white-majority high schools. Similarly, Hurwitz and Lee (2018) observed greater grade inflation among white, Asian, wealthy, and private school students than among students from low-income families and students in public schools.

There are several possible reasons grade inflation occurs in high schools. Some researchers argue that one reason is that high school students are taking advanced coursework that may include “bonus” points that boost their HSGPA (Camara et al., 2004; Hurwitz & Lee, 2018). Subjectivity in grade assignment among teachers also plays a role within and between schools. For example, some teachers assign grades more strictly, while others are more lenient. Gershenson (2018) also argued that teachers may be motivated to provide positive evaluations of student performance not only to satisfy students and parents but also to enhance the reputation of their schools or classrooms.

In recent years, grade inflation has become more pronounced, especially after the COVID-19 pandemic. Because of the COVID-19 outbreak, most American schools transitioned to remote and distance learning in spring 2020 (U.S. Department of Education, NCES, NAEP, 2022b). In response, some school districts moved away from the traditional A–F grading policy to more flexible policies implemented by districts, schools, or classroom teachers (Arundel, 2020; Cano, 2020; Sawchuk, 2020). Grading policies included pass/fail grades, credit/no credit grades, and “do no harm” grading policies (Castro et al., 2020). These changes in mode of instruction and assignment of grades raise concerns about how grades were assigned during this time, and the reliability and accuracy of grades from this period deserve careful consideration. Moreover, grades given during the pandemic may be more a function of district or school policies than accurate reflections of differences in academic achievement across students (Sanchez & Moore, 2022).

With access to additional electronic devices while learning at home during the pandemic, some students may have used multiple devices to check or change answers while completing assignments or exams (Schramm et al., 2021). Consequently, these students may have received higher grades on exams than they would have otherwise. According to Gonzalez et al. (2020), higher grades during remote schooling may be correlated with cheating on online exams. Moreover, students from low-income families may lack basic technology access, such as access to high-speed internet and an adequate number of digital devices, thereby perpetuating social inequities (Herold, 2020). This may have resulted in students from higher-income families receiving artificially inflated grades because of their greater access to technology that allows them to check answers.

These circumstances have increased the uncertainty in evaluating students' achievement during the COVID-19 pandemic. An early case study has revealed some evidence that high school grades improved slightly during COVID-19 (Schramm et al., 2021), and additional research has found that grade inflation became more apparent in 2020 and 2021 (Sanchez & Moore, 2022).

Grade inflation is potentially problematic for students, postsecondary institutions and employers, and society at large (Finefter-Rosenbluh & Levinson, 2015; Silva et al., 2023). For students, inflated grades can create a false sense of proficiency, leading students to believe that they have mastered core content skills (Chowdhury, 2018; Finefter-Rosenbluh & Levinson, 2015). As a result, students may study less, and parents may not understand that their children may need help to catch up (Gershenson, 2018). Grade inflation may prevent students from reaching their full potential (Gershenson, 2018) and subsequently may reduce educational opportunities. For example, some students may take less rigorous courses and subjects in which they can receive higher grades in order to boost HSGPA (Chowdhury, 2018).

Additionally, grade inflation increases the rate at which underprepared high school students enter college, increasing the risk that these students will later drop out of college (Gershenson, 2018). Inflated grades may also influence postsecondary institutions and employment decisions (Finefter-Rosenbluh & Levinson, 2015). Grade inflation may provide misleading information to colleges and employers who use grades as indices of ability and content mastery (Gershenson, 2018).

Grade inflation diminishes the ability of postsecondary institutions to distinguish among prospective students (Finefter-Rosenbluh & Levinson, 2015; Godfrey, 2011; Silva et al, 2023). Similarly, employers who use inflated grades as a criterion in making hiring decisions may not be able to make meaningful distinctions among job applicants; likewise, they may not be able to tell whether an applicant has truly acquired the skills or knowledge required for the job (Finefter-Rosenbluh & Levinson, 2015).

Finally, grade inflation poses societal problems because it may increase social disparities and inequities (Chowdhury, 2018; Finefter-Rosenbluh & Levinson, 2015). Students from families with high socioeconomic status and those attending private or affluent high schools are more likely to receive inflated grades (Gershenson, 2018; Nata et al., 2014; Neves et al., 2017). More recent research has found that students at schools with higher percentages of traditionally underserved students experienced higher rates of grade inflation and students at schools with higher percentages of students eligible for free or reduced-price lunch experienced higher grade inflation (Sanchez & Moore, 2022). These two studies examined affluence slightly differently and found somewhat divergent results. That said, when privileged students receive inflated grades, they may also receive additional unearned advantages in college and graduate admissions, further entrenching their elite status. Although these students are not directly responsible for this situation, this unearned advantage reinforces inequalities (Finefter-Rosenbluh & Levinson, 2015).

Grade inflation also weakens the predictive validity of HSGPA (Zhang & Sanchez, 2013). The ceiling effect of grades (when students score at or near the maximum for the HSGPA distribution) makes it difficult to compare the academic performances of different students, thereby reducing the practical range of HSGPA. As more students approach the “ceiling,” less variability in grades is observed, which leads to less predictive power (Chan et al., 2007; Hurwitz & Lee, 2018).

Much research has focused on the predictive power of HSGPA and standardized admissions test scores (e.g., ACT and SAT). Although the findings consistently demonstrate that HSGPA and test scores are highly correlated (Zhang & Sanchez, 2013), conclusions diverge when it comes to the predictive power of HSGPA and test scores. Some research indicates that HSGPA is a better predictor of college completion, college cumulative GPA, and first-year grades than college admissions tests (Allensworth & Clark, 2020; Bowen et al., 2009; Galla et al., 2019; Geiser & Santelices, 2007; Zwick, 2006). For example, a study that employed a sample of 80,000 first-year students in the University of California system found that HSGPA is consistently the strongest predictor of four-year college outcomes, such as cumulative college grades and graduation (Geiser & Santelices, 2007). A 1999 study of nearly 150,000 first-year students illustrated that HSGPA was more predictive of college completion than admissions tests (Bowen et al., 2009). More recently, Galla et al. (2019) replicated the 1999 predictive validity study findings using a national sample of 47,303 students who applied to college in the 2009–2010 academic year. This was later confirmed by Allensworth and Clark (2020).

Other studies have found that test scores are more predictive than HSGPA. For example, Ramist et al. (1994) examined data from 45 colleges to demonstrate that SAT scores were more predictive of individual college course grades than HSGPA. More recently, Gershenson (2018) used a sample of nearly all high school students in North Carolina from 2005 to 2016 to show that Algebra 1 end-of-course exam scores predict ACT math scores much better than do high school course grades.

HSGPA and ACT scores have different predictive utility depending on the postsecondary outcome examined. For example, HSGPA was slightly more accurate than ACT scores in predicting whether students earn a 2.00 or higher first-year college GPA (FYGPA; ACT, 2022; Noble & Sawyer, 2002). Yet the ACT Composite score and HSGPA were equally accurate in predicting whether students earn a 3.00 or higher FYGPA (ACT, 2022). Likewise, HSGPA is better than the ACT Composite score in predicting minimal success (retention through the first year and attaining a 2.0 or higher FYGPA in college), while the ACT score is better than HSGPA at predicting high-level success (retention through first year and attaining a 3.5 or higher FYGPA) and very high-level success (retention through first year and attaining a 3.7 or higher FYGPA). In addition, ACT Composite scores had incremental validity beyond HSGPA alone (Sawyer, 2010).

However, it is undeniable that together, HSGPA and test scores are more predictive of future success in college than either predictor alone (ACT, 1997; ACT, 2022; Bridgeman et al., 2008; Camara & Echternacht, 2000; Kobrin et al., 2008; Mattern & Patterson, 2011; Noble & Sawyer, 2002; Sawyer, 2010; Westrick et al., 2015; Westrick et al., 2019; Willingham et al., 1990; Zwick, 2006). Moreover, HSGPA and test scores demonstrate strong contributions in predicting post-secondary success across all race/ethnicity and gender groups (Bridgeman et al., 2008).

Although the predictive validity of HSGPA and test scores on postsecondary outcomes after enrollment has been extensively established, it is noteworthy that relatively little research has been done on predicting college enrollment using HSGPA and test scores (ACT, 2010; ACT, 2022). Much research has indicated that college enrollment is positively correlated with high school grades (Okpych & Courtney, 2017; Zhang & Sanchez, 2013). However, with the increase in grade inflation, the longitudinal predictive power of HSGPA alone, test scores alone, and the combination of HSGPA and test scores to predict college enrollment deserve to be explored further. This study is an extension of Sanchez and Moore's (2022) study of the predictive validity of HSGPA and ACT scores. This study employs multilevel logistic regression to examine the predictive power of HSGPA and ACT test scores to predict postsecondary enrollment between 2010 and 2021, including students who tested during the pandemic.

The study addresses the following research questions:

1. Has the predictive power of HSGPA on postsecondary enrollment changed over time?
2. Has the predictive power of the ACT Composite score on postsecondary enrollment changed over time?
3. Has the predictive power of HSGPA and ACT Composite scores combined on postsecondary enrollment changed over time?
4. Does a model which incorporates only HSGPA, only ACT Composite scores, or both best predict postsecondary enrollment?

Methods

Analytical Sample

The present research incorporates student data from the 2010 to 2021 ACT-tested high school graduating cohorts. Between 2010 and 2020, we included every other year due to computational limitations. The 2021 cohort was included to explore the change in predictive validity post-pandemic. This data includes the most recent ACT scores for students who took the ACT more than once. The sample was constrained to public high schools that were matched to 2- and 4-year college enrollment data from the National Student Clearinghouse.[2] Students in the sample either took the ACT on a national test day or through a state or district contract. Only schools with at least 30 tested students each year were included to ensure the stability of multilevel modeling estimates. As such, the individual year statistics may not match those of the official graduating class. The study sample consisted of 16,323,815 students.

Measures

Student demographics. As part of the ACT registration process, students were asked to report certain demographic information. In this study, we used the following student characteristics: race/ethnicity, gender, and family income.

Course grade information. Students were also asked to provide information related to courses they took in high school and their grades for each course. Self-reported grades in up to 23 courses in English, mathematics, social studies, and natural science were averaged to calculate students' cumulative HSGPA. Evidence has shown that students' self-reported HSGPA is highly correlated with students' transcript GPA (Sanchez & Buddin, 2015). Additionally, self-reported data has been shown to be a good substitute for transcript-reported grades for research purposes (Camara et al., 2004; Kuncel et al., 2005; Shaw & Mattern, 2009).

Enrollment information. Enrollment data for the fall after high school graduation was retrieved from the National Student Clearinghouse (NSC). ACT-tested students in the sample were matched to NSC records.

Data Analysis

We started by describing students' characteristics and the number of schools. We then used hierarchical logistic regression with the adaptive Gauss-Hermite quadrature approximation method to estimate postsecondary enrollment for each year (see Appendix).[3] In the multilevel model, Level 1 is students and Level 2 is schools. Students were nested in schools. Enrollment was regressed on HSGPA, ACT Composite score, test type (i.e., national vs. state and district testing), race/ethnicity, gender, and family income.[4]

The Level 2 intercepts were allowed to vary across schools. Nakagawa and Shielzeth (2013) proposed a simple method of obtaining pseudo $\boldsymbol{R^2}$ in multilevel logistic regression, which computes the variance of the predicted outcomes using their logit form. We calculated the marginal and conditional $\boldsymbol{R^2}$ to signify goodness-of-fit of the models. A marginal $\boldsymbol{R^2}$ is based on the fixed effects only, while a conditional $\boldsymbol{R^2}$ is based on both the fixed and random effects (Huang, 2022; Nakagawa & Shielzeth, 2013).[5] The conditional $\boldsymbol{R^2}$ value represents the total model variance explained at both Level 1 and Level 2. The marginal $\boldsymbol{R^2}$ represents the percentage of student-level variance explained by our models. HSGPA and ACT Composite score were standardized across all years. Missing data on family income was imputed 5 times using multiple imputation. Multiple imputation was conducted using the multivariate normal distribution in SAS Proc Impute. The multiple imputation model included parental income, race/ethnicity, gender, HSGPA, and ACT Composite score. One model was run per imputation in R, and then the results were pooled to give final estimates. The data analysis for this study was performed using R (R Core Team, 2022).

Results

Descriptive Statistics

Table 1 summarizes the number of schools and student characteristics in the analyses. From 2010 to 2021, the number of schools ranged from 19,283 to 22,700. Across years, there were slightly more female students than male students. Among these students, the percentage of Black students decreased from 13.5% to 10.7% from 2010 to 2021 and the number of White students decreased from 63.2% to 61.1%. The proportion of Asian students and Hispanic students increased from 2010 to 2020 but dropped slightly in 2021. From 2010 until 2021, the proportion of students from low-income families (defined as students from a family with an income less than $36,000 per year) decreased, while the proportion of students from high-income families (those coming from a family with an income greater than $100,000 per year) increased. College enrollment increased from 27.3% in 2010 to 32.7% in 2021. Students' ACT Composite scores increased by 0.6 scale score points between 2010 to 2021, while students' HSGPA steadily increased from 2010 to 2021, with an especially pronounced increase in recent years.

In the study sample, the percentages of students taking the ACT as part of the National testing program (administered on Saturdays) decreased from 82.3% in 2010 to 62.4% in 2021, while the percentage of students who participated in the State and District testing program (typically during a school day) increased from 17.7% in 2010 to 37.6% in 2021. In 2016, about 30% of the graduating class's most recent record was from a State and District testing program. The State and District testing program administers the ACT to nearly all students within a state or district. The ACT National testing program is more likely to be used by college-bound students who plan to use ACT scores as part of their college application package. The number of students who use the National testing program has decreased; one possible contributor to this change (in addition to the rise of State and District testing) is the growth of test-optional policies before and, importantly, after the COVID-19 pandemic. On March 11, 2020, the World Health Organization declared COVID-19 a global pandemic (WHO, 2020). In the United States, ACT canceled the April, June, and July 2020 national test administrations and resumed limited testing in June 2020. As a result of the pandemic, many post-secondary institutions instituted test-optional policies.

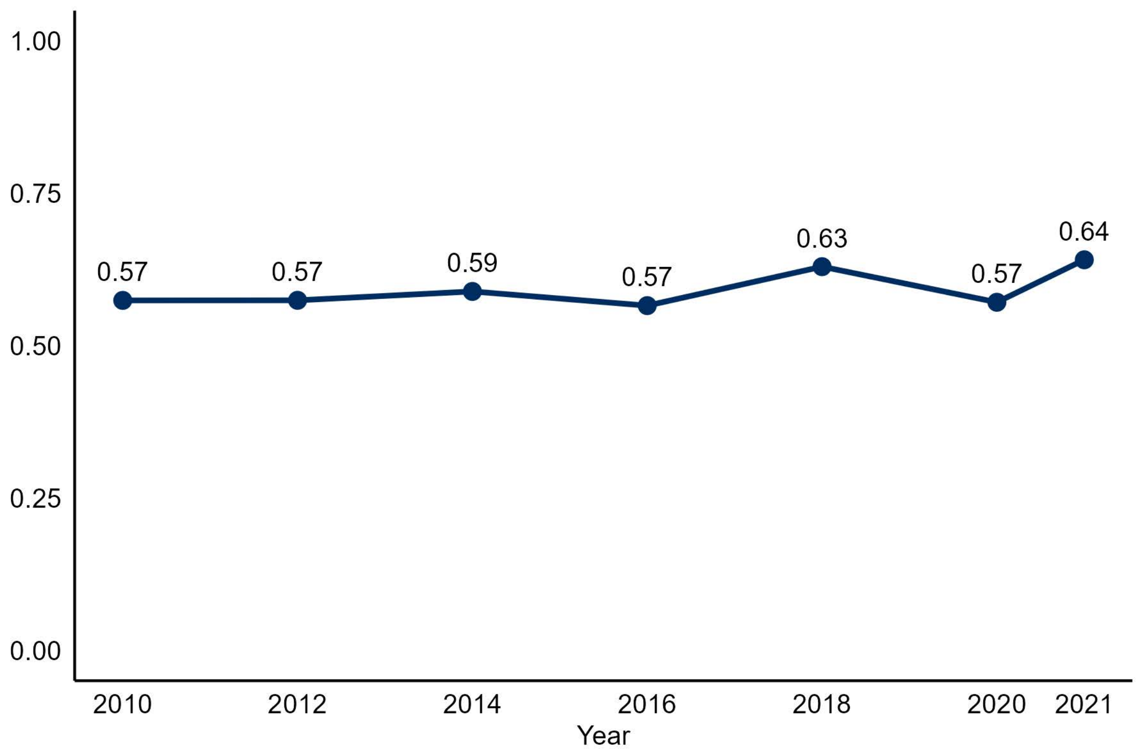
Table 1. Descriptive Statistics

Characteristic	2010	2012	2014	2016	2018	2020	2021
Number of students	1,353,918	1,424,173	1,522,907	1,644,802	1,367,430	1,014,662	748,592
Number of high schools	21,111	21,890	22,375	22,700	22,248	21,448	19,283
Testing program N (%)							
National	82.3%	82.4%	77.3%	70.3%	73.1%	75.1%	62.4%
State and District	17.7%	17.6%	22.7%	29.7%	26.9%	24.9%	37.6%
Race/ethnicity N (%)							
Asian	4.3%	4.2%	4.6%	4.8%	5.5%	5.8%	5.3%
Black	13.5%	13.3%	13.0%	12.8%	12.2%	11.6%	10.7%
Hispanic	9.9%	13.8%	15.1%	16.1%	16.2%	16.0%	12.8%
White	63.2%	59.7%	57.7%	55.7%	55.5%	56.4%	61.1%
Other	3.7%	4.4%	5.0%	5.3%	5.7%	5.9%	5.7%
Prefer not to respond	2.5%	3.6%	3.5%	3.6%	3.3%	3.2%	3.0%
Missing	2.9%	0.8%	1.1%	1.6%	1.7%	1.0%	1.4%
Student gender N (%)							
Female	55.5%	55.3%	54.8%	53.9%	54.9%	56.4%	54.0%
Male	44.4%	44.6%	44.8%	44.9%	44.6%	43.2%	44.4%
Other/missing	0.1%	0.2%	0.4%	1.1%	0.4%	0.4%	1.6%
Enrolled in college N (%)							
Yes	72.7%	71.6%	71.8%	67.8%	71.2%	68.8%	67.3%
No	27.3%	28.4%	28.2%	32.2%	28.8%	31.2%	32.7%
Family income N (%)							
< $36K	27.5%	25.8%	25.1%	24.2%	22.1%	18.8%	15.9%
$36K–$60K	18.6%	17.2%	17.0%	16.9%	15.7%	13.8%	12.4%
$60K–$100K	19.7%	18.8%	18.7%	18.5%	18.1%	17.1%	16.7%
> $100K	14.2%	16.0%	18.1%	20.0%	23.9%	26.7%	30.0%
Missing	20.0%	22.2%	21.2%	20.4%	20.2%	23.6%	24.9%
ACT Composite mean (SD)	21.2 (5.20)	21.2 (5.23)	21.3 (5.35)	21.3 (5.48)	21.6 (5.65)	21.9 (5.83)	21.8 (5.97)
HSGPA mean (SD)	3.20 (0.64)	3.23 (0.63)	3.24 (0.63)	3.25 (0.63)	3.33 (0.61)	3.41 (0.58)	3.43 (0.59)

Q1: Has the Predictive Power of HSGPA on Postsecondary Enrollment Changed Over Time?

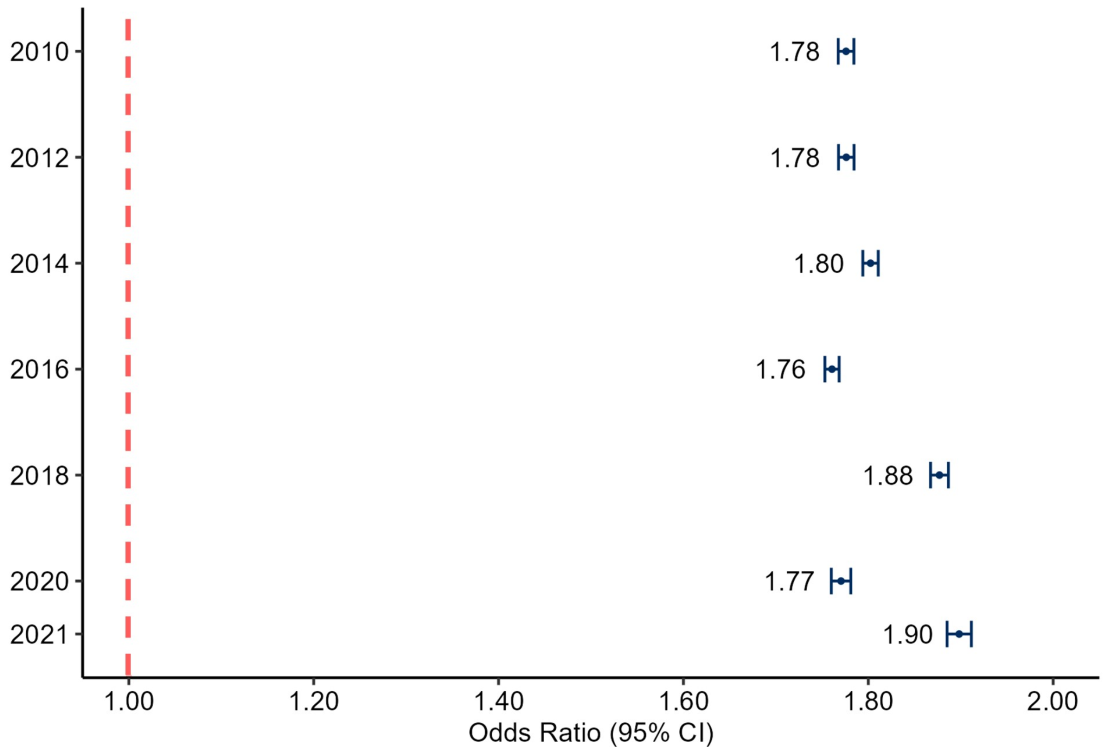
Figure 1 shows the standardized coefficients of HSGPA on postsecondary enrollment from 2010 to 2021, controlling for test type, gender, race/ethnicity, and family income. From 2010 to 2016, the predictive power of HSGPA changed little. In 2018, the predictive power of HSGPA increased from 0.57 in 2016 to 0.63 in 2018. However, it decreased to previous levels in 2020 and increased again in 2021 to its peak. Figure 2 presents the odds ratios and 95% confidence intervals of HSGPA on postsecondary enrollment from 2010 to 2021. It shows the same pattern, in which the predictive power of HSGPA changed more dramatically starting in 2018 and 2021.

Figure 1. Standardized Coefficients of HSGPA from 2010 to 2021



Note: For 2020, one of the five imputed data sets failed to meet one of two convergence criteria. In that imputation, the optimizer convergence criterion was met but the gradient convergence criterion was not. We calculated the pooled coefficient with the remaining four imputations, and the coefficient was the same within three decimal places. Since there was no practical difference, we report the results from all five imputations.

Figure 2. Odds Ratios of HSGPA from 2010 to 2021



Note: For 2020, one of the four imputed data sets failed to meet one of two convergence criteria. In that imputation, the optimizer convergence criterion was met but the gradient convergence criterion was not. We calculated the pooled coefficient with the remaining four imputations, and the coefficient was the same within three decimal places. Since there was no practical difference, we report the results from all five imputations.

Q2: Has the Predictive Power of the ACT Composite score on Postsecondary Enrollment Changed Over Time?

Figure 3 shows the standardized coefficients of the ACT Composite score in predicting postsecondary enrollment from 2010 to 2021, controlling for test type, gender, race/ethnicity, and family income. The standardized coefficient decreased from 0.68 to 0.49 between 2010 and 2021. It reached its lowest coefficient in 2020 during the pandemic. Figure 4 shows the odds ratios of the ACT Composite score in predicting postsecondary enrollment from 2010 to 2021. In 2010, the odds ratio was 1.97, indicating that with one standard deviation score increase on the ACT Composite score, the odds of enrollment increased by 97%.[6] However, the odds ratio dropped to 1.64 in 2021. The decrease in standardized coefficients and odds ratios indicates that the predictive power of the ACT Composite score on postsecondary enrollment has changed over time.

Figure 3. Standardized Coefficients of the ACT Composite Score from 2010 to 2021

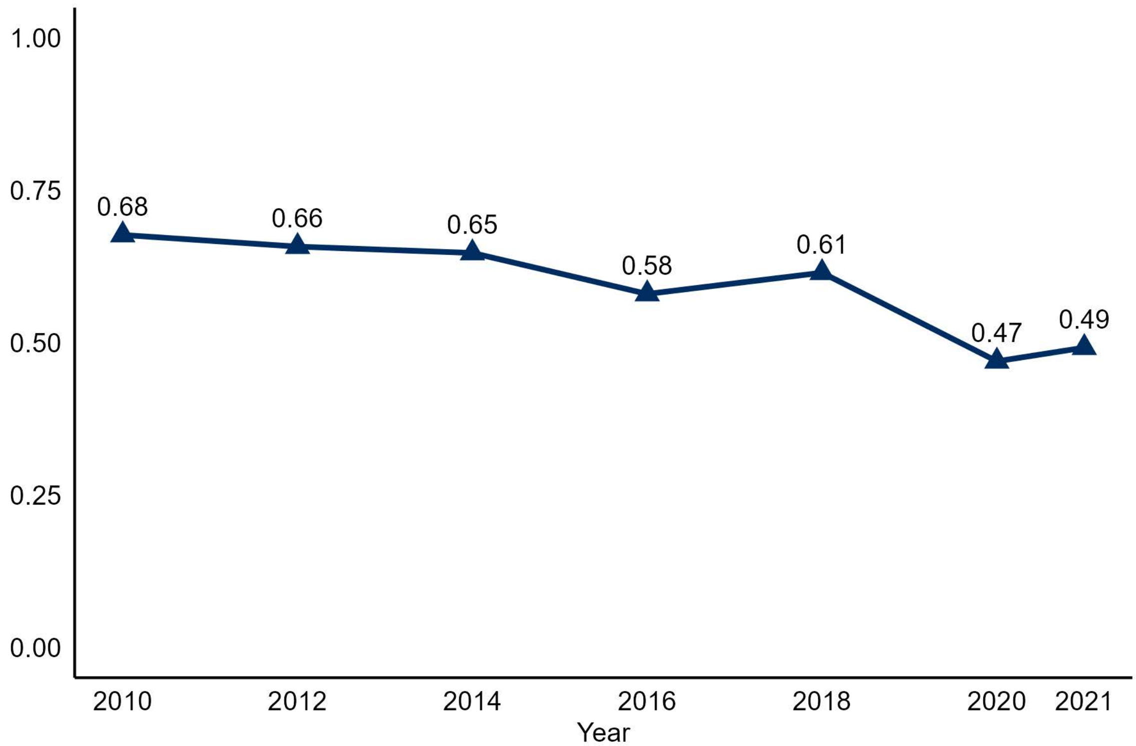
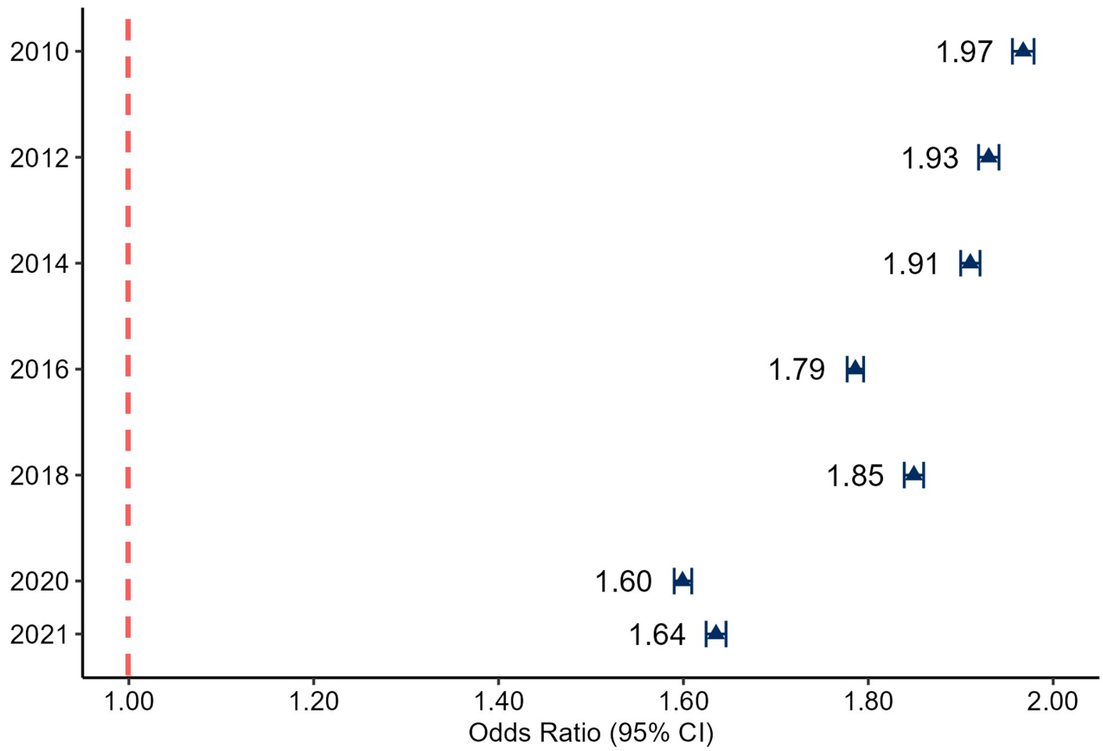


Figure 4. Odds Ratios of ACT Composite Score from 2010 to 2021



Q3: Has the Predictive Power of Using Both HSGPA and ACT Composite Scores on Postsecondary Enrollment Changed Over Time?

Figure 5 and Figure 6 show the standardized coefficients and odds ratios of HSGPA and ACT Composite scores in predicting postsecondary enrollment from 2010 to 2021, while controlling for test type, gender, race/ethnicity, and family income. From 2010 to 2021, the HSGPA coefficient increased from 0.40 to 0.51, and the odds ratios of HSGPA increased from 1.49 to 1.67. During the same period, the coefficients of ACT Composite scores decreased from 0.43 to 0.24, and the odds ratios of ACT Composite score coefficients decreased from 1.53 to 1.27. Before 2014, the ACT Composite score was slightly more predictive of postsecondary enrollment than HSGPA. After 2014, HSGPA was more predictive of postsecondary enrollment than the ACT Composite score. In addition, the difference in the predictive power of HSGPA and the ACT Composite score has widened since 2014. The gap between the predictive power of the ACT Composite score and HSGPA became more pronounced after 2018. This may be because of the growth of test-optional policies. As the use of the ACT has decreased in importance during recent admissions cycles, it is logical that its predictive power would also decrease. Similarly, as HSGPA has grown in importance in recent admissions cycles, its predictive power should also increase.

Figure 5. Standardized Coefficients of HSGPA and ACT Composite Score from 2010 to 2021

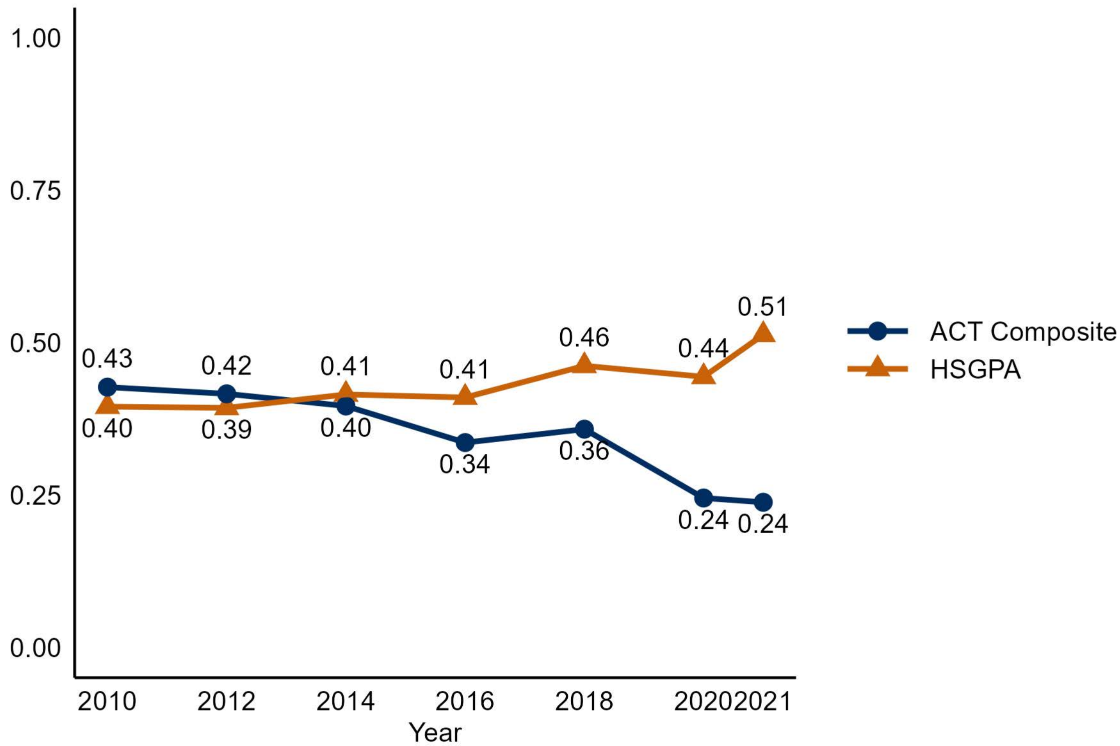
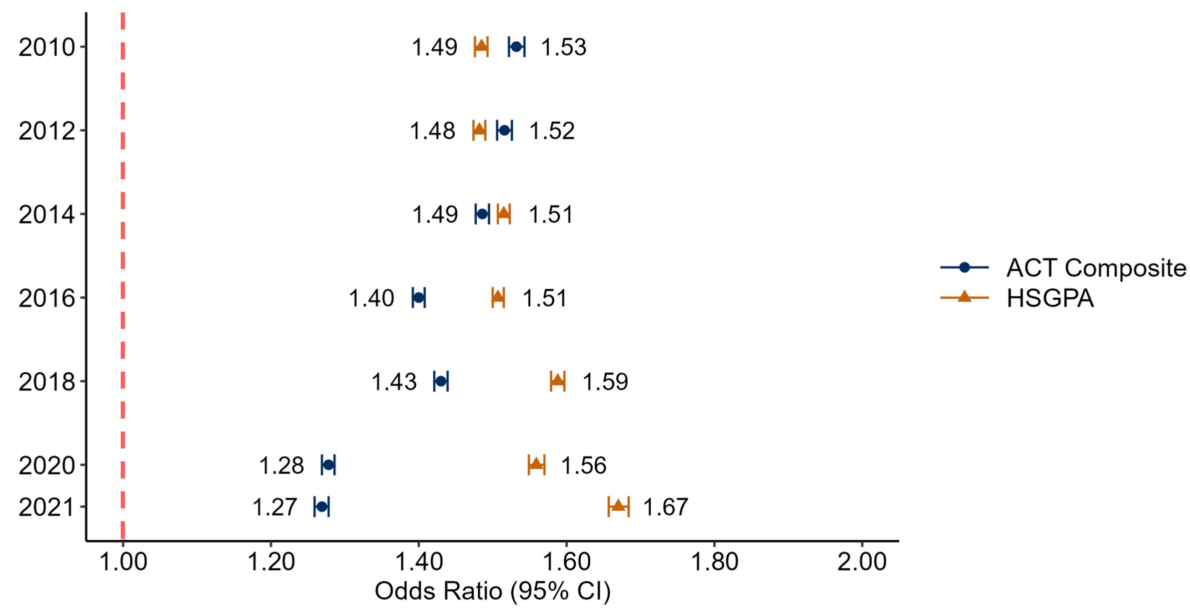


Figure 6. Odds Ratios of HSGPA and ACT Composite score from 2010 to 2021



Note: The odds ratio for 2014 and 2016 for HSGPA are the same when rounded to two decimal places.

In 2020, both the predictive power of HSGPA and the ACT Composite score in predicting postsecondary enrollment declined; however, the predictive power of the ACT Composite score declined more dramatically than did that of HSGPA. This decline may be related to the dramatic changes required during the COVID-19 pandemic. Overall, HSGPA has more predictive power than the ACT Composite score.

Q4: Does a Model Which Incorporates Only HSGPA, Only ACT Composite, Or Both Best Predict Postsecondary Enrollment?

Figure 7 shows the conditional R^2 from hierarchical logistic regression models of HSGPA alone, ACT Composite score alone, and HSGPA and ACT Composite score together predicting postsecondary enrollment from 2010 to 2021 while controlling for test type, gender, race/ethnicity, and family income. The conditional R^2 for the three models steadily increased from 2010 to 2018, then dropped in 2020 and 2021. The model with both predictors always had the largest R^2 value in all years examined. In other words, while HSGPA alone was more predictive than ACT Composite score alone in predicting postsecondary enrollment, using both measures of academic achievement together was more effective at predicting post-secondary enrollment. This finding is consistent with previous research. The conditional R^2 for the ACT Composite–alone model and HSGPA-alone model were similar between 2010 and 2016. In years where they differed, the difference in conditional R^2 was very small, no more than 0.02.

Figure 7. Conditional R^2 of HSGPA and ACT Composite Score from 2010 to 2021

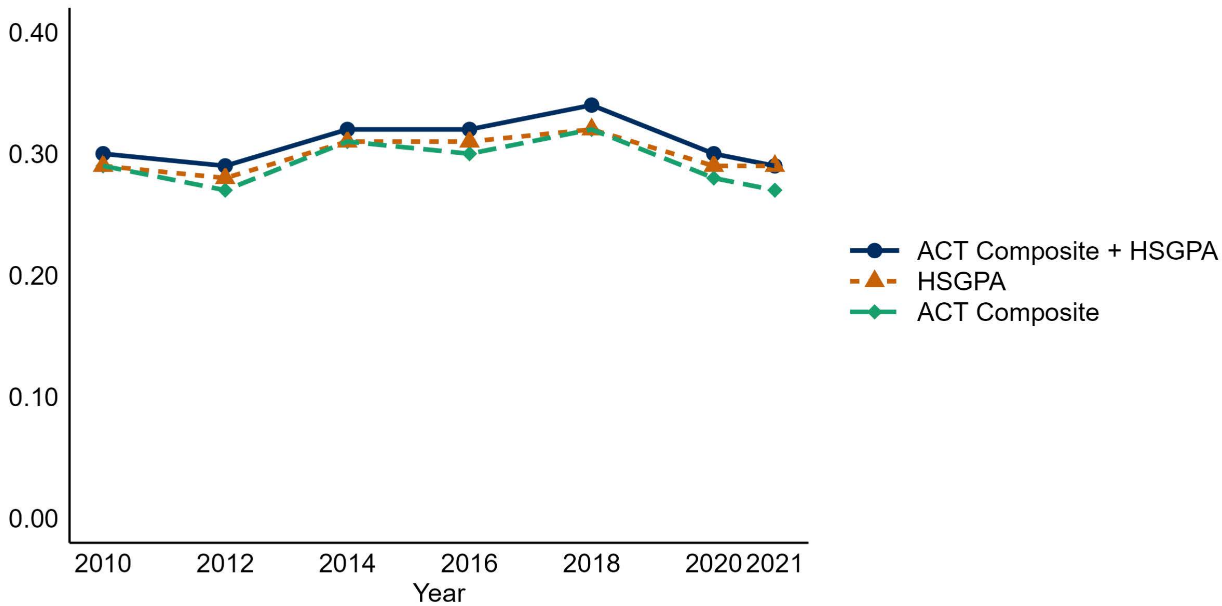
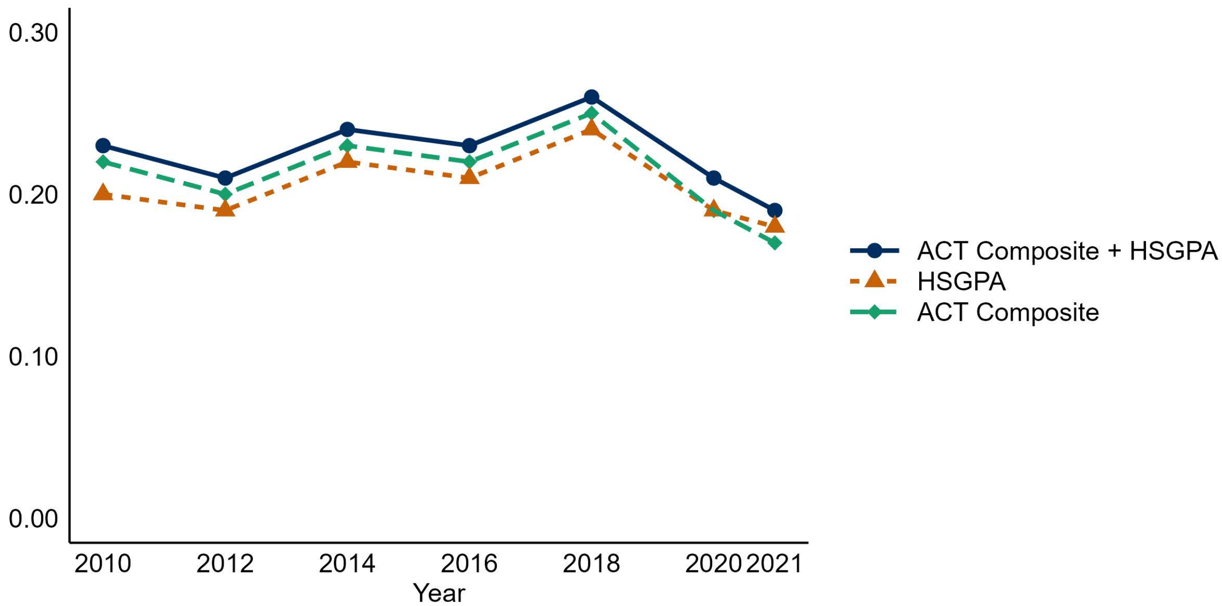


Figure 8 shows the marginal R^2 from hierarchical logistic regression models of HSGPA alone, ACT Composite score alone, and HSGPA and ACT Composite score together predicting postsecondary enrollment from 2010 to 2021 while controlling for test type, gender, race/ethnicity, and family income. As found in the conditional R^2 models, ACT Composite score combined with HSGPA was more predictive of postsecondary enrollment across the years examined. Here again, while the marginal R^2 for each model differed slightly, there may not be a practical difference in predictive validity.

Figure 8. Marginal R^2 of HSGPA and ACT Composite Score from 2010 to 2021



Discussion

This study provided evidence of changes in the predictive validity of HSGPA and ACT Composite score before and during the first year of the pandemic. This study found little practical difference in the predictive validity of the three models examined (HSGPA, ACT Composite, and both HSGPA and ACT Composite). It is possible that we found these results because we included student level covariates that had similar explanatory power across models. In this study, we used data from 2010 to 2021 to explore the predictive power of HSGPA and ACT Composite score on postsecondary enrollment using hierarchical logistic regression.

We first explored the change in the predictive power of HSGPA from 2010 to 2021. From the results of the hierarchical logistic regression, we saw evidence of the predictive power of HSGPA on postsecondary enrollment changing over time. From 2010 to 2021, the predictive power of HSGPA has steadily increased, increasing to its highest value in 2021. We then explored the change in the predictive power of the ACT Composite score from 2010 to 2021. In contrast to the performance of the predictive power of HSGPA, the predictive power of the ACT Composite score has decreased over time, reaching its lowest value in 2021.

In this analysis, we also compared the predictive power of HSGPA alone, ACT Composite score alone, and HSGPA and ACT Composite score together on postsecondary enrollment from 2010 to 2021. We found evidence that HSGPA currently has more predictive power for postsecondary enrollment than the ACT Composite score after accounting for students' characteristics and school effects. In the years examined, HSGPA was not always the stronger predictor when compared to the ACT Composite score in predicting postsecondary enrollment. Before 2014, the ACT Composite score had stronger predictive power than HSGPA. After 2014, HSGPA had more predictive power than the ACT Composite score, and the gap in predictive power between HSGPA and the ACT Composite score in predicting postsecondary enrollment has increased since 2014.

There could be several potential reasons for this trend. First, test-optional policies introduced by postsecondary institutions meant that students were no longer required to submit their ACT scores as part of their application for postsecondary institutions. In a test-optional postsecondary institution application, HSGPA became the primary, and at times only, quantitative measure of student achievement. Based on data from the Integrated Postsecondary Education Data System (U.S. Department of Education, National Center for Education Statistics, Integrated Postsecondary Education Data System, 2023), the number of postsecondary institutions requiring ACT or SAT test scores steadily decreased from 2010 (1,183) through 2019 (985). There were more dramatic decreases in the number of postsecondary institutions requiring test scores in 2020 (562) and 2021 (163). Therefore, HSGPA received more attention than test scores.

Second, COVID-19 sped up the adoption of test-optional policies. During COVID-19, most high schools transitioned to remote or distance learning. Most postsecondary institutions instituted test-optional policies because of students' limited access to ACT and SAT testing. Moreover, there may have been changes in the ways in which HSGPA and test scores were interpreted and used for decision making in the admissions process. In addition, students' perceptions of the value of a postsecondary education may be changing over time. Both of the latter points deserve further study.

As the role of test scores in admissions has changed in recent years, the importance and high-stakes nature of the use of HSGPA for admissions highlight the need for valid and reliable grades. As the importance of HSGPA increases in postsecondary enrollment, there is also evidence that grade inflation has been increasing at a significant rate in recent years. This raises concerns about the way HSGPA is understood and used by postsecondary institutions. We must make sure HSGPA remains a valid indicator in the absence of test scores. This is of particular concern if underprepared students are entering postsecondary education and experiencing less favorable outcomes.

As prior studies have demonstrated, there is greater predictive validity of test scores for higher levels of success in college (e.g., successive level of first-year college GPA), but both measures of student achievement have uses depending upon their application. In this study, the three models examined were found to have similar predictive power on enrollment in *any* postsecondary institution. We must bear in mind, however, that these models predict enrollment at both 2- and 4-year institutions. This criterion of continuing education after high school is useful for guiding high school students but should be coupled with what we know about the predictive validity of both measures for other postsecondary outcomes such as college GPA, retention, and degree completion.

This study clearly demonstrated that using HSGPA and ACT Composite score combined is more effective for predicting enrollment than using HSGPA alone, as may be the case in test-optional admissions policies. HSGPA and ACT scores show different aspects of students' achievement and therefore provide complementary information. Being able to use both HSGPA and a standardized test score such as an ACT score provides a better understanding of student achievement and content mastery. For those reasons, we recommend the use of both HSGPA and ACT Composite score in predicting postsecondary enrollment.

Limitations

As noted, this study was concerned with predicting students' enrollment in either a 2- or 4-year institution. Most two-year institutions have open-admissions policies, which means that ACT scores might not be required or used in the admissions process. This study found similar predictive validity for HSGPA and ACT Composite score when used alone and together. If we were to change the scope of the question to include only 4-year institutions, the results would likely change. To test this assertion, we reran the three models to predict 4-year enrollment in 2021. In that analysis, we found that the use of both measures simultaneously accounted for a greater percentage of variance in enrollment (about 25%) than did using either HSGPA or ACT Composite alone (21% and 22%, respectively). This suggests that when we focus on enrollment in 4-year institutions, where admissions decisions are typically more selective than in 2-year institutions, using both measures of achievement is a better option, consistent with the overall recommendations of this study.

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Appendix

Table A1. HLM Model Coefficients: HSGPA Only

Characteristic		Coefficients 2010	2012	2014	2016	2018	2020	2021
Intercept		1.405***	1.222***	1.486***	1.322***	1.498***	1.227***	1.141***
HSGPA		0.574***	0.574***	0.589***	0.566***	0.630***	0.571***	0.641***
Test type	State and District	−1.234***	−1.218***	−1.262***	−1.169***	−1.272***	−1.204***	−0.794***
Gender	Male	−0.116***	−0.149***	−0.209***	−0.200***	−0.275***	−0.284***	−0.261***
	Other/missing	−0.289***	−0.478***	−1.094***	−0.676***	−0.352***	−0.409***	−0.366***
Race	Black	0.234***	0.286***	0.168***	0.129***	0.166***	0.153***	0.191***
	Hispanic	−0.146***	−0.029*	−0.120***	−0.081***	−0.080***	−0.090***	−0.128***
	Missing	−0.312***	0.047	−0.120***	−0.113***	−0.104***	−0.059*	−0.111**
	Other	−0.033*	0.037*	−0.073***	−0.092***	−0.106***	−0.102***	−0.119***
	Prefer not to respond	−0.147***	−0.014	−0.139***	−0.147***	−0.221***	−0.185***	−0.195***
	White	0.128***	0.206***	0.037**	0.028**	0.000	−0.022	−0.063***
Family income	Linear	0.395***	0.361***	0.371***	0.307***	0.370***	0.292***	0.331***
	Quadratic	−0.101***	−0.081***	−0.073***	−0.091***	−0.073***	−0.074***	−0.065***
	Cubic	−0.001	−0.006	0.003	0.001	−0.002	−0.003	−0.002

Note: * p < 0.05, ** p < 0.01, ***p < 0.001; the reference categories in the model were National testing program, female, and Asian.

Table A2. HLM Model Odds Ratios: HSGPA Only

Characteristic		Odds Ratios						
		2010	2012	2014	2016	2018	2020	2021
Intercept		4.077***	3.392***	4.421***	3.750***	4.474***	3.410***	3.130***
HSGPA		1.776***	1.776***	1.802***	1.761***	1.877***	1.770***	1.898***
Test type	State and District	0.291***	0.296***	0.283***	0.311***	0.280***	0.300***	0.452***
Gender	Male	0.890***	0.862***	0.811***	0.819***	0.760***	0.753***	0.771***
	Other/missing	0.749***	0.620***	0.335***	0.509***	0.703***	0.664***	0.694***
Race	Black	1.264***	1.332***	1.183***	1.137***	1.181***	1.165***	1.211***
	Hispanic	0.864***	0.971*	0.887***	0.922***	0.923***	0.914***	0.880***
	Missing	0.732***	1.049	0.887***	0.894***	0.902***	0.942*	0.895**
	Other	0.967*	1.038*	0.930***	0.912***	0.899***	0.903***	0.888***
	Prefer not to respond	0.864***	0.987	0.870***	0.863***	0.801***	0.831***	0.823***
	White	1.136***	1.228***	1.038**	1.029**	1.000	0.978	0.939***
Family income	Linear	1.484***	1.435***	1.449***	1.360***	1.448***	1.339***	1.392***
	Quadratic	0.904***	0.922***	0.929***	0.913***	0.929***	0.928***	0.937***
	Cubic	0.999	0.994	1.003	1.001	0.998	0.997	0.998

Note: * $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$; the reference categories in the model were National testing program, female, and Asian.

Table A3. HLM Model Coefficients: ACT Composite Only

Characteristic		Coefficients						
		2010	2012	2014	2016	2018	2020	2021
Intercept		1.572***	1.436***	1.730***	1.532***	1.742***	1.446***	1.425***
ACT Composite		0.677***	0.658***	0.647***	0.580***	0.615***	0.469***	0.492***
Test type	State and District	−1.369***	−1.353***	−1.386***	−1.279***	−1.369***	−1.298***	−0.846***
Gender	Male	−0.253***	−0.291***	−0.360***	−0.347***	−0.442***	−0.430***	−0.439***
	Other/missing	−0.462***	−0.577***	−1.148***	−0.748***	−0.411***	−0.561***	−0.614***
Race	Black	0.267***	0.291***	0.153***	0.128***	0.186***	0.186***	0.215***
	Hispanic	−0.118***	−0.047***	−0.158***	−0.093***	−0.071***	−0.058***	−0.101***
	Missing	−0.230***	0.022	−0.183***	−0.136***	−0.136***	−0.028	−0.036
	Other	−0.151***	−0.080***	−0.201***	−0.174***	−0.172***	−0.121***	−0.145***
	Prefer not to respond	−0.265***	−0.115***	−0.261***	−0.227***	−0.281***	−0.207***	−0.220***
	White	0.030*	0.089***	−0.090***	−0.054***	−0.063***	−0.025*	−0.073***
Family income	Linear	0.340***	0.319***	0.335***	0.283***	0.338***	0.282***	0.345***
	Quadratic	−0.114***	−0.089***	−0.083***	−0.100***	−0.093***	−0.095***	−0.096***
	Cubic	−0.009	−0.015**	−0.006	−0.008	−0.013*	−0.008	−0.012

Note: * $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$; the reference categories in the model were National testing program, female, and Asian.

Table A4. HLM Model Odds Ratios: ACT Composite Only

Characteristic		Odds Ratios 2010	2012	2014	2016	2018	2020	2021
Intercept		4.815***	4.203***	5.639***	4.628***	5.707***	4.244***	4.159***
ACT Composite		1.968***	1.930***	1.910***	1.786***	1.849***	1.599***	1.635***
Test type	State and District	0.254***	0.259***	0.250***	0.278***	0.254***	0.273***	0.429***
Gender	Male	0.777***	0.747***	0.698***	0.706***	0.642***	0.651***	0.645***
	Other/missing	0.630***	0.562***	0.317***	0.473***	0.663***	0.571***	0.541***
Race	Black	1.306***	1.338***	1.165***	1.136***	1.204***	1.205***	1.240***
	Hispanic	0.889***	0.955***	0.854***	0.911***	0.931***	0.944***	0.904***
	Missing	0.794***	1.022	0.832***	0.873***	0.872***	0.972	0.964
	Other	0.860***	0.923***	0.818***	0.840***	0.842***	0.886***	0.865***
	Prefer not to respond	0.767***	0.891***	0.770***	0.797***	0.755***	0.813***	0.803***
	White	1.030	1.094***	0.914***	0.947***	0.939***	0.975*	0.930***
Family income	Linear	1.404***	1.376***	1.398***	1.327***	1.403***	1.325***	1.413***
	Quadratic	0.892***	0.915***	0.920***	0.905***	0.911***	0.910***	0.908***
	Cubic	0.991	0.985**	0.994	0.992	0.987*	0.992	0.988

Note: * $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$; the reference categories in the model were National testing program, female, and Asian.

Table A5. HLM Model Coefficients: ACT Composite and HSGPA

Characteristic		Coefficients 2010	2012	2014	2016	2018	2020	2021
Intercept		1.434***	1.263***	1.533***	1.339***	1.506***	1.214***	1.130***
HSGPA		0.395***	0.393***	0.415***	0.410***	0.462***	0.444***	0.513***
ACT Composite		0.427***	0.416***	0.396***	0.336***	0.358***	0.245***	0.238***
Test type	School and District	−1.207***	−1.193***	−1.227***	−1.141***	−1.232***	−1.176***	−0.765***
Gender	Male	−0.160***	−0.198***	−0.258***	−0.240***	−0.320***	−0.318***	−0.295***
	Other/missing	−0.341***	−0.516***	−1.127***	−0.719***	−0.369***	−0.459***	−0.452***
Race	Black	0.388***	0.431***	0.298***	0.253***	0.318***	0.284***	0.324***
	Hispanic	−0.045**	0.054***	−0.048*	−0.001	0.019	0.000	−0.036*
	Missing	−0.199***	0.129***	−0.061***	−0.037	−0.025	0.030	0.009
	Other	−0.024	0.050**	−0.067***	−0.064***	−0.062***	−0.047**	−0.062***
	Prefer not to respond	−0.168***	−0.012	−0.148***	−0.133***	−0.189***	−0.149***	−0.160***
	White	0.114***	0.191***	0.015	0.031**	0.02	0.019	−0.017
Family income	Linear	0.303***	0.281***	0.291***	0.235***	0.287***	0.231***	0.272***
	Quadratic	−0.104***	−0.082***	−0.076***	−0.092***	−0.080***	−0.081***	−0.072***
	Cubic	−0.007	−0.012*	−0.003	−0.004	−0.008	−0.007	−0.008

Note: * $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$; the reference categories in the model were National testing program, female, and Asian.

Table A6. HLM Model Odds Ratios: ACT Composite and HSGPA

Characteristic		Odds Ratios						
		2010	2012	2014	2016	2018	2020	2021
Intercept		4.195***	3.536***	4.633***	3.815***	4.510***	3.367***	3.097***
HSGPA		1.485***	1.482***	1.515***	1.507***	1.588***	1.559***	1.670***
ACT Composite		1.532***	1.516***	1.486***	1.400***	1.430***	1.278***	1.269***
Test type	State and District	0.299***	0.303***	0.293***	0.320***	0.292***	0.308***	0.465***
Gender	Male	0.852***	0.821***	0.773***	0.786***	0.726***	0.728***	0.745***
	Other/missing	0.711***	0.597***	0.324***	0.487***	0.691***	0.632***	0.637***
Race	Black	1.474***	1.539***	1.347***	1.288***	1.374***	1.329***	1.382***
	Hispanic	0.956**	1.056***	0.953***	0.999	1.019	1.000	0.965***
	Missing	0.819***	1.138***	0.941*	0.964	0.975	1.031	1.010
	Other	0.976	1.051**	0.935***	0.938***	0.940***	0.954**	0.940**
	Prefer not to respond	0.845***	0.988	0.863***	0.876***	0.828***	0.862***	0.853***
	White	1.121***	1.210***	1.016	1.031**	1.020	1.020	0.983
Family income	Linear	1.354***	1.324***	1.337***	1.265***	1.332***	1.260***	1.313***
	Quadratic	0.901***	0.921***	0.927***	0.912***	0.923***	0.923***	0.930***
	Cubic	0.993	0.988*	0.997	0.996	0.992	0.993	0.992

Note: * $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$; the reference categories in the model were National testing program, female, and Asian.

Notes

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[1] HSGPA is reported on a scale of 0.0 to 4.0. A letter grade of A was defined as an HSGPA of 3.5 or higher, a letter grade of B was defined as an HSGPA between 2.5 and 3.5, a letter grade of C was defined as an HSGPA between 1.5 and 2.5, a letter grade of D was defined as an HSGPA between 1.0 and 1.5, and an HSGPA below 1.0 was considered an F.

[2] The National Student Clearinghouse is a nonprofit education service whose database contains enrollment information for 97% of students at postsecondary institutions (https://nscresearchcenter.org/current-term-enrollment-estimates/).

[3] To deal with nonconvergence issues, we changed the default optimization method from Nelder-Mead optimization to the quadratic approximation approach.

[4] Family income was included in the models as an ordered factor. In R, ordered factors in logistic regression are tested for higher order terms. As such, the models included a test for the linear, quadratic, and cubic terms.

[5] The simplified equations from Huang (2022) are used. The marginal $\boldsymbol{R^2}$ formula: $R_M^2 = \frac{\sigma^2_{Fixed\ effects}}{\sigma^2_{Fixed\ effects}+\tau_{00}+\frac{\pi^2}{3}}$, where σ^2 is the variance of fixed effects and τ_{00} is the variance of the random intercept. The conditional $\boldsymbol{R^2}$ formula: $R_C^2 = \frac{\sigma^2\sigma^2_{Fixed\ effects}+\tau_{00}}{\sigma^2\sigma^2_{Fixed\ effects}+\tau_{00}+\frac{\pi^2}{3}}$, where σ^2 is the variance of fixed effects and τ_{00} is the variance of the random intercept.

[6] Across years, the standard deviation for ACT Composite score was about 1.0.

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