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Narrowing Enrollment Gaps for Underrepresented College Students in Engineering: Using Contextualized Admissions Measures to Predict Student Success*

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Previous studies show that contextualized measures of high school achievement – in other words, how well students performed relative to their high school peers – can help identify students who have the potential to succeed in college, and thus can serve as a key measure in holistic admissions. Building upon previous work, this study further examines whether contextualized measures of high school achievement may help identify students who have the potential to succeed in engineering programs, especially among traditionally underrepresented students in engineering (defined in our paper as low-SES students, underrepresented students of color, and women). Based on longitudinal data from a Midwestern state's Department of Education database, this study finds that contextualized measures of high school performance are significantly associated with students' college performance – for all students in engineering, as well as across our three subsamples of traditionally underrepresented students. These findings have important implications for incorporating contextualized measures of high school performance when making undergraduate admissions decisions in engineering programs, to help better identify applicants from traditionally underrepresented student populations in engineering. This is particularly crucial as admissions offices move toward more holistic and test-optional practices.

Keywords: engineering; holistic admissions; equity; student success; college access; low-income students; women; underrepresented students of color

1. Introduction

STEM education at the K-12 level is not equally accessible to all students, due to a wide range of structural inequities in the U.S. education system. With school funding determined by local property taxes, lower-SES and underrepresented students of color tend to be concentrated in schools with low levels of financial and pedagogical resources [1]. Students in these schools therefore experience multiple disadvantages, including lack of access to advanced STEM coursework, larger class sizes, and dearth of tailored support from teachers [2–4]. Given this context, evaluating students in college admissions solely using their raw measures of high school achievement (such as raw SAT scores, raw high school GPA, or how many advanced STEM courses students took at their high school) may exacerbate existing inequities, without considering the educational opportunities that were available to them.

In light of these problems, institutions are seeking ways to increase equity and diversity in college admissions: Holistic review aims to level the playing field among students who had access to different levels of educational opportunities and resources, by evaluating an applicant's achievement within the context of the opportunities that had been available to them within their own high school, family, and neighborhood context. The literature shows that admissions officers who evaluate students based on *contextualized* measures of high school performance (for example, evaluating an applicant's high school grades and standardized test scores in relation to peers at the applicant's own high school) are more likely to admit low-SES students compared to admission officers who rely solely on *raw* criteria to make admission decisions [5–7].

Many students who do not have the highest raw credentials in the applicant pool may still have the potential to succeed and thrive in college engineering programs. Research drawing upon a state-wide sample of students in public four-year institutions found that contextualized measures of high school performance were strongly associated with various college success indicators such as first-year college GPA, first-year retention, and college graduation within four years [8]. These trends were also con-

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firmed, in sub-sample analyses drawing upon the same state-wide sample, for women, underrepresented students of color, and low-income students [9]. That said, the lack of empirical evidence on whether contextualized measures of high school performance are related to college success in the engineering context may still cause admissions officers and engineering faculty to be reluctant to admit students who do not display the highest raw high school performance within their applicant pool.

Our study therefore examines whether students who have outperformed their peers within their own high school have the potential to thrive in college engineering programs. The aim of our paper is not to compare raw and contextualized measures of high school performance, and identify which displays a stronger relationship with college success; Rather, we aim to examine the extent to which contextualized measures – which incorporate important information that raw measures do not – are associated with college success, and can therefore serve as legitimate criteria in holistic engineering admissions practices that helps expand educational opportunities to student populations who are traditionally underrepresented in engineering programs. Examining these questions is particularly timely, given the literature presents ample evidence on efforts that can be done at the K-12 level to make engineering more equitable and diverse [10, 11], but provides comparatively little insight into factors admissions officers can and should take into account to achieve this aim [12, 13].

Our study therefore delves into the following research questions: (1) Are contextualized measures of high school performance (i.e. high school GPA, standardized test scores, curriculum rigor in math and science subjects) used in holistic review associated with successful college outcomes in engineering? (2) Are the aforementioned contextualized measures of high school performance associated with successful college outcomes for underrepresented student populations (i.e. low-income, women, minoritized students of color) in engineering programs?

2. Literature Review

2.1 K-12 Disparities and Enrollment Gaps in STEM Admissions

Gaps in enrollment are pronounced among underrepresented students of color and low-income students majoring in STEM. In part, these enrollment gaps can be attributed to disparities in K-12 opportunities among students of different race/ethnicities and socioeconomic status, especially at more selective universities [14, 15]. As high school GPA and test scores have historically weighed significantly in college admissions processes, the literature shows a link between SES, GPA, and test scores, further setting back disadvantaged students [16]. Studies show that students from the highest income quartiles enrolled in undergraduate engineering programs at higher rates than their lower-income peers [17–19]. Further, engineering students tend to come from more privileged high schools, further demonstrating disparities in enrollment for students of lower socioeconomic backgrounds [18, 20, 21].

First-generation college students – who are most often low-SES and/or underrepresented students of color as well – face multiple barriers to enrolling in engineering programs. Among these barriers include having limited access to high school credentials shown to be valued by admissions officers, as well as limited access to timely, tailored support on how to navigate the admissions process, and also differences in parental ability to help cover costs of tuition [22–24]. Considering the heterogeneity of educational resources and academic rigor across the high schools and the various backgrounds students are coming from, evaluating students' raw performance will disregard the educational resources that were available to them, the barriers they faced, the challenges that they overcame, and would therefore lower the changes of these students going onto engineering programs and exacerbate the existing structural inequalities.

2.2 The STEM Admissions Landscape

2.2.1 Underrepresented Students of Color and Low-Income Students

Underrepresented students of color and low-SES students still remain a minority in engineering majors at the undergraduate level. To examine the extent of this phenomenon, it is useful to examine the proportion of students obtaining engineering degrees by race/ethnicity and class (as opposed to acceptance rates, as a large proportion of students in the U.S. do not choose their majors until several years after starting college). According to the most recent available statistics provided by the American Society for Engineering Education, underrepresented minorities (defined as Black, Latinx, American Indians, and Alaska Natives) comprise only 16.5% of total engineering bachelor's degrees awarded between the 2020–2021 academic year [25]. As for low-income students, data for the class of 2014 showed that only 9% of students who attended low-income schools (public, non-charter) earned a STEM degree within six years of graduating high school [26]. In comparison, 18% of students from higher-income schools earned a

STEM degree. Of the 9% of students from low-income schools who earned a STEM degree, only 13% of them earned an engineering degree – compared to the 19% of their higher-income peers who also earned an engineering degree.

These numbers should be evaluated in light of the various barriers that complicate applying to and studying in a STEM major. Research shows that admissions officers at a selective institution showed the tendency to prioritize high levels of raw math and science achievement when evaluating engineering applicants [27]. Moreover, undergraduate engineering programs often have lengthy and strict course requirements, which disadvantage students who do not display adequate STEM-related credentials at the high school level [13, 28]. These structural arrangements likely work against low-income, underrepresented students of color, in light of the disparity of STEM-related opportunities offered among various high schools around the country.

For required classes such as physics and calculus, lacking the educational background or high school credentials for admission to four-year engineering programs can set students back in the admission process, requiring them to first enter community college instead – in turn, this can extend the cost and time of obtaining their engineering degree [13]. Most likely, these students beginning in community college are significantly less likely to earn a bachelor's degree in engineering than if they had begun at a four-year college [29, 30]. Although community colleges are instrumental in enrolling students from underrepresented backgrounds, students may still be disadvantaged in applying for four-year engineering programs, further exacerbating issues of underrepresented students of color and low-income students being ill-prepared for engineering programs.

A correlational study based on admissions officers evaluating engineering applicants to Brown University examined what admissions officers prioritize when making admissions decisions in engineering, and found a tendency to favor high levels of math and science achievement as well as high school GPA. These factors significantly changed admissions outcomes on the part of students, but were found to be correlated with socioeconomic status–thus working as barriers to disadvantaged student populations [27]. Based on its analysis, the study recommends against evaluating applicants based on only one criterion such as SAT scores or GPA [27].

2.2.2 Women

The number of women awarded undergraduate engineering degrees has more than doubled over the past decade, from 11,340 in 1998 to 27,600 in 2018; and yet, these figures only comprise 24% of all engineering bachelor's degrees awarded in the 2020–2021 academic year, leaving women still vastly underrepresented among engineering majors [25]. To better understand the meaning behind these figures, they should be examined in light of the high school to college engineering pipeline. A potential explanation for the comparative underrepresentation of women in the field of engineering is the gender gap in standardized tests: College Board data shows that men consistently have higher SAT math scores from 1972 to 2016 [31], while women have on average scored higher than men on Evidence-Based Reading and Writing [32]. ACT data shows similar results, with men having higher math scores. Interestingly, however, there are no such gender gaps in high school grades and course-taking rigor regarding STEM subjects: Research shows that gender differences in advanced-level math and science course-taking have more or less ceased to exist since the mid-to-late 1990s [1, 33]. Studies also find that girls typically have higher grades than their male peers across all their high school subjects, including math and science [34]. Jacob [35] attributes this phenomenon to the fact that high school GPA and standardized test scores are measuring different components of academic achievement. It is possible that institutions are placing more importance on metrics (i.e. standardized test scores) that happen to favor male applicants, thus disadvantaging women applicants with higher grades [36].

2.3 Institutional Efforts to Address STEM and Engineering Enrollment Gaps

Institutions have adopted a multitude of strategies to help combat enrollment gaps of underrepresented students in STEM programs, ranging from a focus on racially inclusive STEM marketing materials to retention and STEM enrichment programs [37]. Other research that focuses on engineering education offers recommendations for institutional interventions such as mentoring at the transition stages between high school and college levels, greater outreach to all stakeholders (i.e., high schoolers, community college students, teachers, and counselors) to help students take engineering degree preparatory courses, and improving parental education on what applying for and obtaining an engineering degree would entail [1]. Further, institutions can better inform students about the operations of colleges, engage in their interests, and offer greater moral support for underrepresented students of color interested in engineering [13].

However, most of these strategies only focus on recruitment, and do not address STEM admissions practices per se. Some studies argue that using additional admission criteria that advantages underrepresented student populations instead of solely relying on traditional criteria commonly used in engineering admissions may help narrow enrollment gaps. For example, one Midwestern university addressed engineering enrollment gaps by strategically identifying affective factors that benefited women in admissions [36]. These affective factors included motivation, propensity, and leadership among women; in comparison, traditional criteria commonly used in engineering admissions such as math and science coursework and standardized test scores favored men, even when women had higher high school metrics overall. These results were presented to major stakeholders in engineering admissions at the university, including recommendations for an increased emphasis on affective factors along with a de-emphasis on standardized math test scores, which resulted in a 5% increase in women enrolled from the previous year, and an additional percentage increase in women enrolled during the subsequent year.

Further institutional efforts to increase equity and diversity of student admits in STEM involve incorporating student context when evaluating student merit. Pontificia Universidad Católica de Chile, for example, created an alternative admissions program for engineering in 2011, which sought out high school students from disadvantaged socioeconomic backgrounds who they determined would not be admitted under traditional admissions standards [7]. These students demonstrated the potential for success through personal attributes such as leadership and resilience, instead of solely based on their standardized test scores. In addition, these students came from municipal or private subsidized schools, which contrasted to the types of students generally admitted through traditional admissions. In the previous admissions year, more than 80% of incoming freshmen came from private, fee-paying high schools that generally enrolled students with the highest standardized test scores, showing the impetus for the creation of this program. Multiple cohorts of students enrolled in the program demonstrated successful academic performance after their first year of college.

Similarly, recognizing that students from educationally disadvantaged backgrounds have fewer opportunities to develop skills measured by traditional admission criteria such as standardized tests and grades, the National Action Council for Minorities in Engineering (NACME) developed the *Vanguard* program [38]. The program evaluates students' creativity, problem-solving and critical thinking skills through in-depth individual interviews and an interactive performance-based assessment process where students were taught new concepts and worked in collaborative teams to solve complex problems. Students admitted through the *Vanguard* program, who might otherwise not have been able to gain admission to participating universities, went on to show high persistence and graduation rates.

Prior research examines the role of contextualized measures in engineering admissions and their effects on the enrollment of low-SES applicants. In one experiment, admissions officers who were provided with robust contextual data on applicants were 25% more likely to admit a low-SES applicant to engineering who had maximized their high school opportunities [5]. Admissions officers who espoused a whole context view of holistic admissions were even more likely to admit the low-SES engineering applicant [6]. With respect to college success, prior research based on a multi-institution state-wide sample of college students suggests that contextualized measures of high school performance are strongly related to college GPA, retention, and graduation [8], and these effects also hold for women, low-income, and underrepresented students of color [9].

Our paper seeks to add to the existing literature by further examining whether contextualized measures also predict college success in engineering. More specifically, we examine whether contextualized measures of high school performance – namely, how well students performed in relation to their high school peers–may help identify students with the potential to succeed in college engineering majors.

3. Data & Methods

To answer these questions, we constructed a dataset drawing upon a medium-sized Midwestern state's Department of Education database (DOE). This data – containing expansive information from the high school to college level – was particularly well-suited to answer our research questions, for several reasons. The state's database included information on high school transcripts for all students who graduated from public high schools from 2010 to 2015 – which translates into more than 27 million observations for over 2.3 million high school students in the state. This allowed us to observe courses taken by individual students throughout their high school career, the grades and credits they received, and student demographics.

We cleaned information on high school course-taking within each student's transcript following an intensive protocol. This was a key process as we found considerable variability in high school courses across transcripts from different high school institutions, as well as those from across different years. We dropped 32% of schools in our original dataset (which accounts for 20% of high school graduates), as these schools did not supply adequate data that fulfilled the standards in our protocol; follow-up analysis shows that the majority of these dropped schools were failed charter schools or alternative high schools. Due to this strict cleaning process, we remain confident that the data used in our study is comparable across different high schools, as well as across different years within the same high school.

The state's database also included extensive information on high school students' performance on the ACT during the 2010–2015 time period, as the state mandated the ACT for all high school juniors during this time. These two aspects of the data enabled us to construct contextualized measures of high school performance that have not been possible with any other large-scale dataset. Finally, the state's DOE database also provides transcript data from all in-state public universities, each of which has at least one ABET-accredited engineering program. This allowed us to match students' high school and college transcripts. The public four-year institutions included in our sample vary in selectivity and size, including selective state flagship and research-intensive institutions; the majority of institutions in our sample are broad-access institutions.

3.1 Sample

Students who satisfied the following conditions were included in our final dataset. First, the student needed to have their first three years of high school transcript data present in the DOE database. This was crucial information for the purposes of our study, as it was used to calculate raw and contextualized measures of high school performance. Second, the student needed to have gone to a public university within their home state. Finally, the student needed to have majored in engineering during their undergraduate career. This resulted in the matching of high school and college transcript data for 77,804 students, which accounts for 75% of in-state college freshmen. Included in the 25% missing rate are students who either went to private high schools or attended a high school that we removed from the sample (i.e., including alternative schools, schools that closed during the collection period, and schools with one or more years of missing data), which amounts to 10% of all high school graduates [39]. Our concurrent analysis comparing sample students and the true in-state freshman at each of our postsecondary institutions showed that the missing data does not noticeably affect the overall demographic makeup of the sample. Therefore, we believe our analytic sample is representative of the whole in-state student population at each of our target institutions.

3.2 Variables

Among many factors admissions officers consider when making admissions decisions is whether an applicant has adequate potential to succeed in college [40]. While student success in the field of engineering can be defined in many different ways, common conceptualizations in the literature include engineering students' college GPA, first-year retention, and graduation [41–43]; moreover, these success indicators are interdependent. Students with low GPAs – particularly during their first year of college–were found to be more likely to drop out of engineering majors in subsequent years [41, 43]. Studies posit this may be because engineering students who receive low college GPAs have low levels of self-efficacy, which in turn leads to lower retention rates: most students who had low GPAs in their first three semesters left engineering – whether voluntarily, or involuntarily pushed out of the major based on academic probation requirements [43]. Lower probabilities of retention and graduation have therefore been identified as a significant problem in four-year college engineering programs, which would also have negative impacts on students' subsequent labor market outcomes [42]. We therefore use first-year college GPA, first-year retention within engineering major, and graduation with an engineering degree within four years as our dependent variables. First-year GPA was operationalized as a student's GPA up until their second fall term. First-year retention within engineering major was constructed as a binary variable showing whether an engineering student remained in the engineering major for the fall term of their second year, and graduation with an engineering degree within four years was a binary variable showing whether a student received an engineering degree by the end of their fourth year.

We further constructed various measures of raw and contextualized high school performance to use as our independent variables of interest. Raw high school GPA, for example, is the GPA for a student's first three years of coursework in high school, which is the timepoint at which admissions officers would see records on applicants' academic achievement. Our operationalization of this variable did not weight grades for more advanced coursework such as honors and AP courses, and we rounded all grades to the closest letter grade. The main reason we choose this approach is because high schools may have different grading practices, and this provides the most common denominator among institutions. For instance, some institutions in our sample do not use gradations in their admission processes (e.g., a B+ is a 3.0, not a 3.3). We also ran additional specifications with gradations for one institution, which yielded nearly identical results compared to the approach of using a rounded GPA. We then created a contextualized high school GPA variable, by subtracting the median score at a student's high school from the raw score, and then dividing by the standard deviation of the score at that school. The resulting contextualized high school GPA variable thus shows how far a student lies from the median student at their own institution. We applied a similar process to create raw and contextualized ACT composite score variables.

We also included independent variables that would allow us to examine the rigor of English, math, and science courses taken by a student during their high school career. We constructed three separate ordinal scales for English, math, and science curriculum level respectively. For every additional course per year that a student had taken in one of these subjects, we added one point to the corresponding subject scale; a further additional point was added for potential AP enrollment, with students able to obtain up to five potential points in total for each of the three subjects. After creating these raw measures of English, math, and science high school curriculum rigor, we proceeded to also create contextualized forms of these variables. For instance, the contextualized score for math curriculum rigor was created by taking a student's highest value for math course level, dividing this by the highest value of math course level offered by the student's high school, and then standardizing this value. Contextualized high school curriculum rigor variables therefore represent how much (in standard deviations) a student progressed through the English, math, and science courses offered by their school.

3.3 Analytic strategy

We ran a series of OLS regression models for our continuous dependent variables (i.e. college GPA), and logistic regression models for our binary dependent variables (i.e. first-year retention within engineering major, graduation with an engineering degree within four years). In terms of student-level characteristics, we controlled for student gender, race/ethnicity, and an indicator for low-income status (a binary indicator of whether a student is a Pell recipient). Pell recipient status is a frequently utilized proxy for income in U.S.-based studies: the Pell grant is a need-based federal financial aid awarded by the U.S. Department of Education to help eligible low-income students pay for the cost of attending college. We also controlled for expenditures per full-time enrolled (FTE) student in terms of district-level characteristics; as well as school urbanicity, percentage of underrepresented students of color, and percentage of students who received free and reduced-price lunch at the school level. To this model specification, we also incorporated fixed effects for institution, college cohort, and institution-by-cohort fixed effects, to prevent unobserved variation at these levels from biasing model estimates [44]. Then we produced our sample of interest, which are engineering students, measured as students who started an engineering major (based on CIP code) in their first fall term at the first higher education institution where they enrolled. Finally, we split our engineering sample into populations of interest (Pell recipients, women, and underrepresented students of color (i.e. Black, Latinx, Hawaiian/Pacific Islander)), to examine how the relationship between contextualized high school performance and college success might differ for different populations within engineering students. The notation for our OLS regression models is as follows:

$$DV = \beta_0 + \beta_1 IV + \beta_2 D + \beta_3 S + FE_\mathrm{i} + \varepsilon$$

where DV stands for continuous dependent variables of interest, IV stands for independent variables of interest, D is a vector of demographic covariates, S is a vector of high school covariates, FE stands for a set of fixed effects, and ε is the error term. Based on the results obtained from this model specification, we also calculated partial eta squared to more easily interpret the strength of relationships between independent and dependent variables in each model, as well as ensure comparability across different models. Partial eta squared reflects the amount of residualized variation in the dependent variable that a single variable of interest can explain in the model.

The notation for our logistic regression models is as follows:

$$DV = log(\tfrac{\pi}{1-\pi}) = \beta_0 + \beta_1 IV + \beta_2 D + \beta_3 S + FE_i$$

where DV stands for dichotomous dependent variables of interest, IV stands for independent variables of interest, D is a vector of demographic covariates, S is a vector of high school covariates, FE stands for a set of fixed effects, and ε is the error term. Because logistic regression models, unlike OLS regression models, do not allow us to calculate partial eta squared effect sizes, we instead ran separate linear regression models with respective dichotomous dependent variables for the sole purpose of calculating partial eta squared for effect size. Because the public four-year institutions in our sample range from selective state flagship to broader-access institutions, for each model, we ran an overall regression for all institutions as well as separate regressions for each individual institution. This allows us to examine the robustness of the relationships between raw and contextualized high school performance and college success across different institutions.

3.4 Limitations

We added a set of fixed effects to our regression models to account for unobserved confounders at the cohort, institution, and institution-by-cohort level, thus helping improve the accuracy of our estimates of the relationship between high school performance and college outcomes. Even so, our study findings should still be interpreted as correlational, not causal. Our study therefore should not be interpreted as evidence that our independent variables directly lead to various indicators of college success, but rather that they tend to be – in varying degrees – associated with indicators of college success. Another problem with drawing causal inference concerns potential selection bias due to the fact that our sample conditions on students who have "succeeded" by enrolling in in-state public institutions. In addition, students coming from wealthier family backgrounds may have more flexibility to select out-of-state institutions compared to low-income students. Consequently, our sample may exhibit a higher proportion of low socioeconomic status (SES) students than what truly represents the overall population. However, addressing this issue can be challenging considering the data that are made available to us. To date, however, there has yet to be a similar large-scale empirical study – whether causal or not – examining the relationship between contextualized high school performance and college success. We therefore believe our study findings supply important evidence to throw light upon this subject.

We also recognize that there is room for further exploration regarding how to operationalize contextualized measures of high school performance, as well as indicators of college success. This study is the result of having considered many potential ways to operationalize these constructs, based on the data we had. However, there are many other ways to measure contextualized high school performance [45, 46] as well as college success [47]; these varying operationalizations may possibly yield different results. We therefore strongly encourage future literature to explore relationships between indicators of high school performance and college success, using various other operationalizations of these constructs.

Another limitation pertains to our operationalization of graduation as a college success indicator. We chose to operationalize this variable as "graduation from college within four years," as this would allow us to include more college cohorts in our sample to examine students' graduation outcomes, based on the data that are available to us. However, many engineering students may need more than four years to graduate. Indeed, our descriptive findings show that four-year graduation rates are relatively lower for engineering students than those from other departments. Whether a student graduates within four years may therefore not be the best indicator of college completion for engineering students, and may bias our estimates of the relationship between students' high school performance and college success. We thus also ran supplemental analysis for cohort 2014–15, for whom we could observe whether students had graduated within five years. The aggregated estimates for all 15 institutions and sub-analyses for three institutions with sufficient cell sizes (institutions F, G, K) show no appreciable difference in coefficients/effect sizes compared to the estimates from corresponding four-year graduation rates models. As a result, we believe the four-year graduation indicator, although not ideal, still provides reliable evidence to help us explore the relationship between contextualized measures and graduation.

4. Results

4.1 Descriptive Findings (Tables 1–3)

Tables 1 and 2 show descriptive statistics for the full sample of students in our dataset, as well as a comparison of our engineering (N = 9,445) and non-engineering (N = 68,359) samples. Compared to the non-engineering sample, the engineering sample has a smaller proportion of underrepresented students of color and a larger proportion of White and Asian students. Over two thirds of our engineering students are men, while over 60 percent of non-engineering students are women in our full sample. Our engineering sample also has a smaller proportion of Pell recipients compared to the non-engineering sample. High school demographics in Table 2 further show that compared to the non-engineering students, engineering students are disproportionately concentrated in schools with lower proportions of underrepresented students of color, and schools with lower proportions of students who received free and reduced-price lunch. On average, engineering students have higher raw and contextualized high school GPAs and higher raw and contextualized ACT composite scores compared to non-engineering students. Engineering students also tend to have taken more rigorous high school math and science courses than their non-engineering peers.

Table 3 shows descriptive statistics for minor-

Table 1. Descriptive statistics of sample

	All		Engineering		Non-Engineering	
Variable	%	N	%	N	%	N
Race/ethnicity						
Asian	5.4	4,217	8.0	758	5.1	3,459
Black	8.9	6,905	5.7	535	9.3	6,370
Latinx	4.4	3,431	3.6	339	4.5	3,092
White	75.1	58,428	76.8	7,254	74.9	51,174
Multiracial	3.9	3,041	3.3	310	4.0	2,731
Haw./Pac. Islander	0.1	54	0.1	10	0.1	44
Unknown	2.2	1,728	2.5	239	2.2	1,489
Gender						
Male	44.4	34,553	78.4	7,400	39.7	27,153
Female	55.6	43,251	21.6	2,045	60.3	41,206
Pell status						
Pell	27.7	21,519	23.7	2,241	28.1	19,278
Non-Pell	72.3	56,285	76.3	7,204	71.9	49,081
High School Urbanicity						
City	18.7	14,522	20.0	1,894	18.5	12,628
Suburb	48.8	37,956	48.3	4,560	48.9	33,396
Town	11.1	8,647	11.2	1,055	11.1	7,592
Rural	21.4	16,679	20.5	1,936	21.6	14,743

Table 2. Descriptive statistics of sample (continued)

	All				Engineering Sample		Non-Engineering Sample	
Variable	N	Mean	Min	Max	N	Mean	N	Mean
High School Demographics								
School % Free/Reduced-Price Lunch	77,787	32.6%	4.5%	99.8%	9,443	30.3%	68,344	32.9%
School % URM	77,787	19.5%	0.0%	100.0%	9,443	17.9%	68,344	19.7%
School Expenditures per FTE	77,787	$9,824	$7,098	$36,954	9,443	$9,781	68,344	$9,830
High School Performance								
High School GPA	77,804	3.42	0.65	4.00	9,445	3.57	68,359	3.40
Contextualized HS GPA*	77,796	0.49	–4.36	3.47	9,443	0.64	68,353	0.47
ACT Composite	77,708	23.47	11.00	36.00	9,435	25.76	68,273	23.15
Contextualized ACT Composite*	77,700	0.62	–2.88	5.42	9,433	1.02	68,267	0.56
Math Level	77,348	4.60	2.00	8.00	9,375	5.61	67,973	4.46
Science Level	77,804	4.80	2.00	9.00	9,445	5.18	68,359	4.75
Contextualized Math Level	77,348	–0.82	–2.97	1.49	9,375	–0.09	67,973	–0.92
Contextualized Science Level	77,804	–0.37	–2.97	2.98	9,445	–0.15	68,359	–0.40
College Success Indicator								
First-Year College GPA	77,803	2.97	0.00	4.00	9,445	2.92	68,358	2.98

Note: Contextualized variables are in standard deviation units.

itized students of color, Pell recipients, and women within our engineering sample, to show how indicators of high school performance and college success differ descriptively for these subgroups. Underrepresented students of color on average have lower high school GPAs and ACT composite scores, both raw and contextualized, compared to Pell recipients and women. Underrepresented students of color also tend to have lower first-year college GPAs, lower retention and graduation rates within engineering major compared to their peers.

4.2 Analytical Findings (Tables 4–8)

Findings reveal that our variables of interest (i.e. raw and contextualized measures of high school GPA, ACT composite scores, and high school science math/science curriculum rigor) are significantly associated with various college success indicators (i.e. first-year college GPA, first-year college retention within engineering, and graduating with an engineering degree within four years). The specific strength of these relationships across institutions in our sample vary, however; we present

Table 3. Descriptive statistics of sample - Engineering students

	Minoritized Students of Color		Pell Recipients		Women		All Engineering Students	
Variable	**N**	**Mean**	**N**	**Mean**	**N**	**Mean**	**N**	**Mean**
High School Performance								
High School GPA	884	3.31	2,241	3.54	2,045	3.73	9,445	3.57
Contextualized HS GPA*	884	0.61	2,240	0.71	2,043	0.84	9,443	0.64
ACT Composite	882	22.27	2,237	24.58	2,045	26.45	9,435	25.76
Contextualized ACT Composite*	882	0.77	2,236	1.00	2,043	1.12	9,433	1.02
College Success Indicators								
1st-year GPA	884	2.48	2,241	2.97	2,045	3.12	9,445	2.92
1st-year Retention Rates (%)	884	62.2%	2,241	79.4%	2,045	76.1%	6,811	72.1%
4-year Graduation Rates (%)	578	12.6%	1,428	25.4%	1,312	38.9%	6,160	29.3%

Note: Contextualized variables are in standard deviation units.

these results in more detail in the section below. It is important to keep in mind that interpretations for coefficients/odds ratios in each model depend on the independent variable in question. Coefficients for models involving raw high school GPA, for example, should be interpreted as the change in the dependent variable associated with a 0.1-point change in high school GPA; coefficients for models involving raw ACT composite scores represent the change in the dependent variable associated with a one-point change in ACT composite scores; coefficients for models with raw high school math/science curriculum rigor show the change in the dependent variable linked to a one-unit increase of raw math/science level attainment. Coefficients for models with contextualized measures, on the other hand, show the change in the dependent variable associated with a one standard deviation unit increase in the independent variable.

4.3 College GPA (Tables 4–5)

Raw measures of high school GPA are significantly associated with first-year GPA across all institutions in our sample; the effect size associated with this relationship is 0.261 for all institutions. Similarly, contextualized measures of high school GPA are also associated with first-year GPA, albeit with a somewhat smaller effect size of 0.197 across all institutions. As Table 4 illustrates, at Institution G, for example, a 0.1-point increase in high school GPA is associated with a 0.127-point increase in first-year GPA and accounts for 29.5% of the residualized variation in a student's first-year GPA. A one standard deviation increase in high

Table 4. Engineering: Coefficients and effect sizes for high school GPA variables and first-year college GPA

		HS GPA		Contextualized HS GPA			ACT Composite		Contextualized ACT Composite	
Inst.	**N**	**Coeff**	**Eff Size**	**Coeff**	**Eff Size**	**N**	**Coeff**	**Eff Size**	**Coeff**	**Eff Size**
Total	9,287	0.110***	0.261	0.652***	0.197	9,277	0.054***	0.062	0.215***	0.048
A	147	0.088***	0.205	0.610***	0.171	147	0.060***	0.076	0.274***	0.079
B	207	0.082***	0.156	0.466***	0.123	207	0.016	0.003	0.034	0.001
C	391	0.110***	0.279	0.783***	0.243	391	0.061***	0.057	0.299***	0.067
D	589	0.111***	0.250	0.711***	0.196	587	0.054***	0.056	0.231***	0.047
E	94	0.106***	0.335	0.747***	0.302	94	0.049*	0.055	0.200	0.043
F	1,736	0.104***	0.181	0.521***	0.120	1,734	0.038***	0.042	0.142***	0.029
G	1,626	0.127***	0.295	0.815***	0.234	1,626	0.046***	0.043	0.193***	0.035
H	105	0.103***	0.296	0.735***	0.278	105	0.069*	0.051	0.355**	0.066
I	672	0.110***	0.327	0.689***	0.268	670	0.075***	0.125	0.321***	0.108
J	200	0.096***	0.315	0.658***	0.261	200	0.070***	0.113	0.311***	0.110
K	1,629	0.232***	0.137	0.283***	0.020	1,629	0.050***	0.053	0.152***	0.026
L	532	0.100***	0.270	0.559***	0.194	531	0.068***	0.099	0.246***	0.068
M	104	0.125***	0.416	0.841***	0.352	103	0.026	0.013	0.118	0.013
N	483	0.108***	0.339	0.573***	0.239	482	0.084***	0.126	0.311***	0.099
O	772	0.105***	0.263	0.752***	0.247	771	0.038***	0.027	0.171***	0.028

Notes: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Each coefficient/effect size represents an individual linear regression model with all covariates and fixed effects.

Table 5. Engineering: Coefficients and effect sizes for high school math and science curriculum rigor levels and first-year college GPA

		Math Level		Contextualized Math Level			Science Level		Contextualized Science Level	
Inst.	**N**	**Coeff**	**Eff Size**	**Coeff**	**Eff Size**	**N**	**Coeff**	**Eff Size**	**Coeff**	**Eff Size**
Total	9,219	0.093***	0.041	0.120***	0.039	9,289	0.095***	0.017	0.089***	0.010
A	148	0.179***	0.131	0.198***	0.115	148	0.055	0.004	0.093	0.011
B	206	0.027	0.003	0.014	0.001	207	0.065	0.004	0.012	0.000
C	391	0.102***	0.037	0.152***	0.052	391	0.126*	0.013	0.130**	0.016
D	589	0.086***	0.039	0.100***	0.030	589	0.136***	0.036	0.111**	0.015
E	94	0.055	0.012	0.122	0.040	94	0.007	0.000	0.063	0.003
F	1,727	0.056***	0.020	0.078***	0.023	1,736	0.064***	0.012	0.063***	0.008
G	1,613	0.084***	0.035	0.108***	0.032	1,626	0.074***	0.010	0.074***	0.007
H	104	0.181	0.054	0.158	0.036	105	0.070	0.002	0.026	0.000
I	668	0.200***	0.139	0.250***	0.131	673	0.193***	0.051	0.217***	0.048
J	199	0.087**	0.044	0.113**	0.042	200	0.127	0.015	0.126	0.018
K	1,608	0.053***	0.014	0.057***	0.009	1,629	0.046***	0.008	0.021	0.001
L	531	0.086***	0.038	0.115***	0.038	532	0.122***	0.024	0.088*	0.010
M	100	0.106	0.037	0.135	0.040	104	0.067	0.004	0.124	0.011
N	477	0.138***	0.083	0.180***	0.079	483	0.146***	0.032	0.135**	0.022
O	764	0.087***	0.034	0.109***	0.030	772	0.104***	0.015	0.055	0.003

Notes: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Each coefficient/effect size represents an individual linear regression model with all covariates and fixed effects.

school GPA from one's high school median, on the other hand, is linked to a 0.815-point increase in first-year GPA, accounting for 23.4% of residualized variation in first-year GPA.

ACT composite scores – in both raw and contextualized form – are also significantly associated with first-year college GPA across the majority of institutions in our sample (Table 4). To continue with Institution G, for instance, a 1-point increase in raw ACT composite scores is associated with a 0.046-point increase in first-year college GPA, which accounts for 4.3% of residualized variation in the dependent variable. A one standard deviation increase in ACT composite scores from one's high school median, on the other hand, is associated with a 0.193 increase in first-year GPA, which accounts for 3.5% of residualized variation. Effect sizes for the relationship between ACT composite scores and college GPA, however, are notably smaller than those observed above for high school GPA (as illustrated by Fig. 1): while overall effect sizes for the relationship between raw and contextualized high school GPA and college GPA are 0.261 and 0.197 respectively, the effect sizes associated with the relationship between raw and contextualized ACT composite scores and college GPA remain 0.062 and 0.048 respectively. This provides evidence that measures related to high school GPA display a stronger relationship with first-year college GPA than do measures related to ACT scores.

Table 5 portrays the relationship between high school math and science curriculum rigor levels and first-year college GPA, respectively. As would be expected from the literature, high school math curriculum level – whether raw or contextualized– displays a statistically significant relationship with first-year college GPA across the majority of institutions in our sample. However, the effect sizes obtained for this relationship are smaller than those obtained for high school GPA and ACT composite scores. Our models produce an overall effect size of 0.041 for the relationship between raw math curriculum level and first-year college GPA, which is noticeably smaller than above-mentioned effect sizes for raw high school GPA (0.261) or raw ACT composite scores (0.062). At Institution G, for example, each unit increase in raw math level attainment accounts for 3.5% of residualized variation in first-year college GPA; each unit increase in contextualized math level attainment accounts for 3.2% of residualized variation. High school science curriculum rigor levels and first-year college GPA display an even weaker relationship – with fewer institutions across our sample showing statistical significance, and even those with significant results showing the smallest effect sizes out of all independent variables of interest tested in our study (0.017 for raw, and 0.010 for contextualized high school science curriculum rigor across all institutions in our engineering sample).

4.4 First-Year Retention Within Engineering (Table 6)

At the majority of institutions in our sample, both raw and contextualized high school GPA are significantly associated with first-year retention;

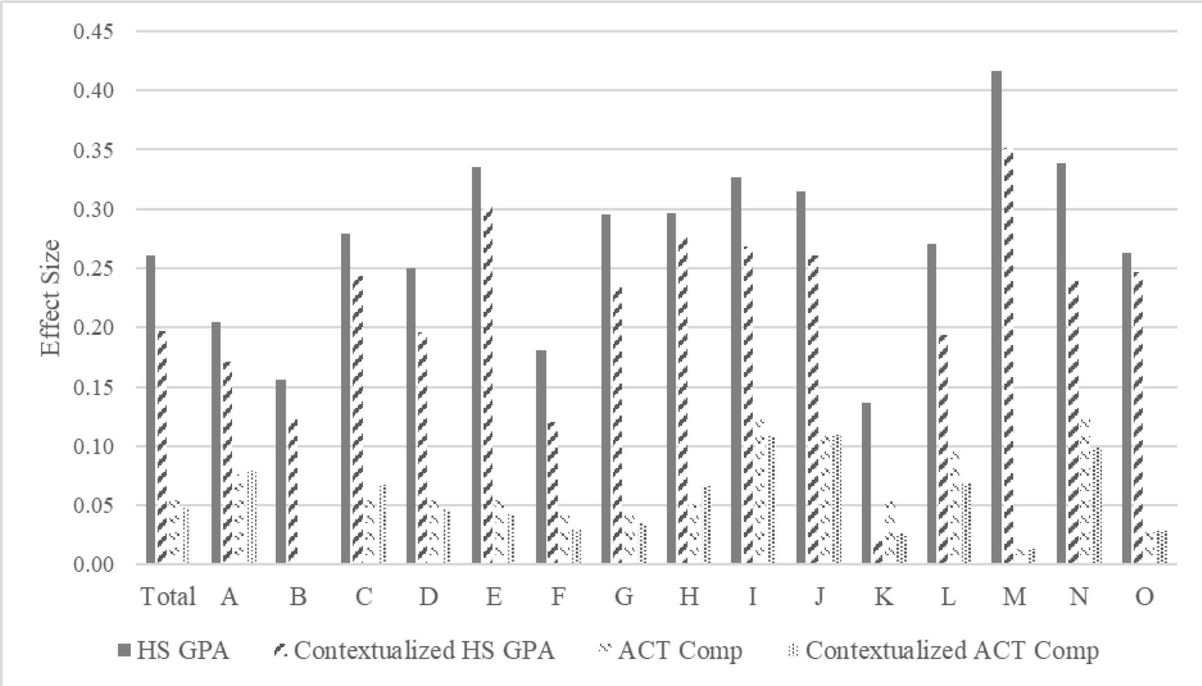

Fig. 1. Effect sizes for high school GPA and ACT composite scores on first-year college GPA.

Table 6. Engineering: Odds ratios and effect sizes for high school GPA variables and first-year retention

		HS GPA		**Contextualized HS GPA**			**ACT Composite**		**Contextualized ACT Composite**	
Inst.	**N**	**Odds Ratio**	**Eff Size**	**Odds Ratio**	**Eff Size**	**N**	**Odds Ratio**	**Eff Size**	**Odds Ratio**	**Eff Size**
Total	9,287	1.119***	0.031	2.022***	0.026	9,277	1.035***	0.003	1.163***	0.002
A	146	1.009	0.000	1.094	0.000	146	0.990	0.000	1.042	0.000
B	207	1.039	0.005	1.473	0.013	207	1.025	0.001	1.007	0.000
C	391	1.110***	0.031	2.604***	0.040	391	1.047	0.004	1.351	0.008
D	587	1.147***	0.045	2.821***	0.049	585	1.091**	0.018	1.584***	0.022
E	88	1.263**	0.132	6.462**	0.156	88	1.132	0.028	2.073*	0.050
F	1,736	1.176***	0.029	2.560***	0.026	1,734	1.018	0.001	1.103	0.001
G	1,622	1.191***	0.052	3.391***	0.046	1,622	1.062**	0.006	1.300**	0.005
H	100	1.109*	0.065	2.096*	0.063	100	1.115	0.029	1.740*	0.036
I	672	1.125***	0.061	2.063***	0.048	670	1.080***	0.022	1.383***	0.018
J	198	1.122**	0.054	1.857*	0.028	198	1.081	0.017	1.229	0.006
K	1,629	0.908	0.001	0.850	0.000	1,629	0.853***	0.024	0.598***	0.015
L	528	1.082**	0.018	1.689**	0.017	527	1.038	0.003	1.082	0.001
M	–	–	–	–	–	–	–	–	–	–
N	483	1.109***	0.039	1.745***	0.028	482	1.063*	0.009	1.225	0.005
O	772	1.130***	0.053	2.385***	0.049	771	1.075***	0.015	1.336**	0.012

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Each odds ratio/effect size represents an individual linear regression model with all covariates and fixed effects. The sample size of engineering students at institution M was very small, and there was not enough variation in first-year retention rates to complete/support a logistic regression; we therefore removed them from the subsample analysis. This institution was still included in the logit model across all institutions (estimates for "Total").

effect sizes obtained for these relationships are generally much smaller compared to those associated with college GPA. At Institution C, for example, a 0.1-point increase in raw high school GPA is associated with 1.110 higher odds of first-year retention (11% higher), accounting for 3.1% of the residualized variation in first-year retention. At the same institution, a one standard deviation increase in high school GPA from one's high school median is associated with 2.604 higher odds of first-year retention, accounting for 4.0% of the residualized variation in first-year retention.

The estimates for the relationship between high school GPA-related measures and first-year college retention are statistically significant for the overall estimates of all institutions in our engineering sample, and the effect size for the relationship between contextualized high school GPA and first-year college retention is 0.026 – which is slightly smaller than the effect size for raw high school GPA and first-year retention (0.031). In contrast, ACT composite scores are not consistently associated with first-year retention across institutions in our sample. Less than half of the institutions in our engineering sample display a significant relationship between raw or contextualized ACT composite scores and first-year retention within the engineering major. Even those institutions showing statistically significant relationships show much smaller effect sizes compared to those obtained for the relationship between high school GPA-related measures and first-year retention. This tendency for high school GPA-related measures to display stronger relationships with college retention than do ACT-related measures has also been noted for models using college GPA as a success indicator. On average, a 1-point increase in raw ACT composite score is associated with 1.035 higher odds (3.5% higher) of first-year retention within engineering major; a one standard deviation increase in ACT composite scores from one's high school median is associated with 1.163 higher odds (16.3% higher) of first-year retention within engineering major.

4.5 Four-Year Graduation Within Engineering (Table 7)

In general, we observe a statistically significant relationship between raw and contextualized measures of high school GPA and four-year graduation across the institutions in our sample. For the majority of institutions in our engineering sample, effect sizes for raw high school GPA are slightly larger than those obtained for its contextualized counterpart in relation to four-year graduation within engineering major. At five institutions in our sample, however, contextualized high school GPA displays an even larger effect size for four-year college graduation than does raw high school GPA. At Institution G, for instance, a 0.1-point increase in raw high school GPA is associated with 1.281 higher odds (28.1% higher) of graduating with an engineering degree within four years, accounting for 7.8% of the residualized variation in the graduation rate; for students with high school GPAs one standard deviation above their high school median GPA, odds of graduating with an engineering degree within four years are approximately six

Table 7. Engineering: Odds ratios and effect sizes for high school GPA variables and four-year college graduation

		HS GPA		**Contextualized HS GPA**			**ACT Composite**		**Contextualized ACT Composite**	
Inst.	**N**	**Odds Ratio**	**Eff Size**	**Odds Ratio**	**Eff Size**	**N**	**Odds Ratio**	**Eff Size**	**Odds Ratio**	**Eff Size**
Total	6,121	1.298***	0.054	5.068***	0.052	6,114	1.111***	0.020	1.611***	0.019
A	105	1.276***	0.111	4.039*	0.074	105	1.123	0.035	1.579	0.024
B	143	1.368***	0.093	8.525***	0.100	143	1.174	0.027	1.914*	0.023
C	245	1.149***	0.049	3.323***	0.059	245	1.103*	0.021	1.694*	0.029
D	375	1.326***	0.060	9.767***	0.068	374	1.150**	0.023	1.820**	0.020
E	40	–	–	–	–	–	–	–	–	–
F	1,139	1.327***	0.052	5.186***	0.046	1,138	1.106***	0.018	1.534***	0.015
G	1,058	1.281***	0.078	6.123***	0.088	1,058	1.099***	0.021	1.570***	0.022
H	46	–	–	–	–	–	–	–	–	–
I	396	1.427***	0.146	10.145***	0.135	394	1.206***	0.076	2.309***	0.071
J	119	–	–	–	–	–	–	–	–	–
K	1,099	1.355***	0.016	2.691***	0.017	1,099	0.982	0.001	1.055	0.000
L	306	1.478***	0.074	9.535***	0.063	305	1.270***	0.065	2.678***	0.058
M		–	–	–	–	–	–	–	–	–
N	304	1.370***	0.103	4.464**	0.063	304	1.297***	0.080	2.872***	0.059
O	508	1.332***	0.060	8.207***	0.057	507	1.170***	0.030	1.943***	0.027

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Each odds ratio/effect size represents an individual linear regression model with all covariates and fixed effects. While we do have estimates for institutions E, H, and J, these estimates may be biased because only 40 students from institution E, 46 students from institution H, and 119 students from institution J qualified as an engineering student. We therefore eliminated these students from our subsample analyses. Observations from these institutions were still included to obtain estimates across all institutions (estimates for "Total"). Also, the sample size of engineering students at institution M was very small, and there was not enough variation four-year college graduation to complete/support a logistic regression; we therefore removed them from the subsample analysis. This institution was still included in the logit model across all institutions (estimates for "Total").

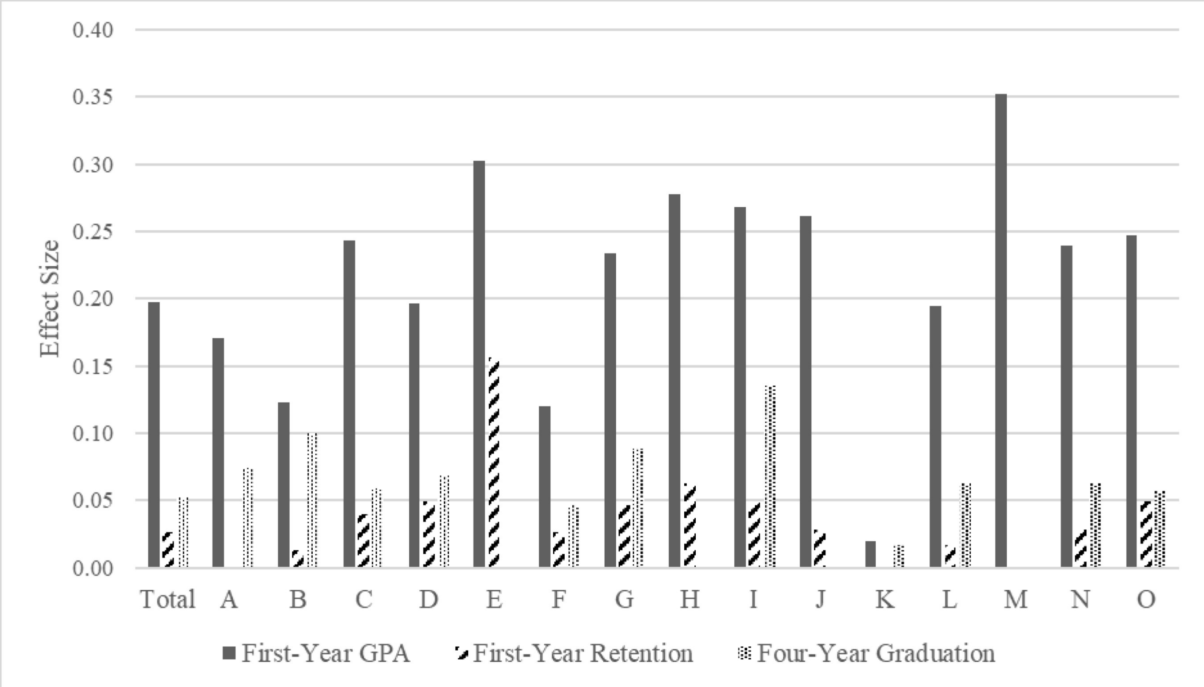

Fig. 2. Effect sizes for contextualized high school GPA on first-year college GPA, retention after the first year, and graduation within four years.

times greater, accounting for an estimated 8.8% of the residualized variation.

Similar to our findings regarding college GPA and first-year retention, four-year graduation also displays a comparatively stronger relationship with high school GPA-related measures than with ACT-related measures. For the overall estimates of the engineering sample, a one unit increase in raw and contextualized high school GPA accounts for 5.4% and 5.2% of the residualized variation in four-year graduation within engineering major, respectively. In contrast, a 1-point increase in ACT composite score and a one standard deviation increase in ACT composite scores from one's high school median account for 2.0% and 1.9% of the residualized variation in four-year graduation in engineering, respectively.

An interesting trend is that both raw and contextualized measures of high school GPA and ACT composite scores are more strongly associated with college persistence as students progress into their college careers. As illustrated in Fig. 2, the strength of the relationship (effect size) between contextualized high school GPA and college GPA is strongest; the effect size is comparatively weaker for four-year graduation, and is the weakest for first-year retention.

4.6 Split Sample Analysis (Table 8)

We further examine how the relationship between contextualized high school performance and college success might differ for different populations within engineering students. Table 8 shows how the relationship between college success indicators and contextualized high school GPA (Panel A), as well as the relationship between college success indicators and contextualized ACT composite scores (Panel B), differ among various subgroups of interest in engineering. Similar to what we witnessed for the overall sample of engineering students, our findings for the Pell recipients, underrepresented students of color, and women also show that contextualized high school GPA is significantly associated with all three college success indicators (first-year college GPA, retention and graduation within engineering major). Coefficients/odds ratios and effect sizes obtained for the split sample analysis are generally slightly smaller than those obtained from the full engineering sample (Panel A). Across all three sub-samples, contextualized ACT composite score is significantly associated with first-year college GPA as well as graduating with an engineering degree within four years (Panel B). For Pell recipients and women, the relationship between contextualized ACT composite score and first-year retention within engineering is not statistically significant.

It is worth noting that the relationships between contextualized ACT composite score and first-year college GPA (and four-year graduation within engineering) are at times stronger in our student subgroups than in our full engineering sample, in

Table 8. Split Sample Analysis: Contextualized high school performance and college success

Panel A: Contextualized HS GPA									
	1-yr GPA			**1-yr Retention**			**4-yr Graduation**		
	Coeff.	**Effect Size**	**N**	**Odds Ratio**	**Effect Size**	**N**	**Odds Ratio**	**Effect Size**	**N**
Pell	0.400***	0.154	2,191	1.347**	0.004	2,136	3.395***	0.029	1,394
URM	0.492***	0.143	873	1.493**	0.012	861	5.517***	0.019	445
Women	0.633***	0.183	2,021	1.992***	0.014	2,009	4.518***	0.040	1,280
Overall	0.652***	0.197	9,287	2.022***	0.026	9,287	5.068***	0.052	6,121
Panel B: Contextualized ACT Composite									
	1-yr GPA			**1-yr Retention**			**4-yr Graduation**		
	Coeff.	**Effect Size**	**N**	**Odds Ratio**	**Effect Size**	**N**	**Odds Ratio**	**Effect Size**	**N**
Pell	0.156***	0.051	2,187	0.954	<0.001	2,132	1.422***	0.011	1,392
URM	0.158***	0.029	871	1.224*	0.005	859	2.103***	0.019	444
Women	0.217***	0.066	2,021	1.150	0.002	2,009	1.387***	0.010	1,280
Overall	0.215***	0.048	9,277	1.163***	0.002	9,277	1.611***	0.019	6,114

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

terms of odds ratio and effect sizes. For instance, one standard deviation increase in ACT composite score from one's high school median is related to a 0.215 point increase in first-year GPA for the full engineering sample, accounting for 4.8% of the residualized variation. In contrast, for female engineering students, a one standard deviation increase in ACT composite score from one's high school median is related to a 0.217 point increase in first-year GPA, accounting for 6.6% of the residualized variation. These estimates suggest that contextualized measures of high school performance are consistently related – or even have a stronger relationship – with college success, for all three traditionally underrepresented student groups in our engineering sample. These findings suggest that contextualized measures of high school performance will be particularly useful in identifying traditionally underrepresented students who have the potential to succeed in engineering programs.

5. Discussion and Implications

Our findings present important implications on the meaningfulness and effectiveness of incorporating contextualized measures into admissions to identify students who have the potential to succeed in college. Our findings are in line with the recommendations from The Standards for Educational and Psychological Testing [48], which underscores the importance of incorporating other variables in addition to raw test scores to avoid inappropriate score interpretations in making high-stakes individual decisions. According to the Standards, test scores should not be used as sole indicators to characterize an individual's competence or attitudes; instead, "multiple sources of information should be used, alternative explanations for test performance should be considered, and the professional judgment of someone familiar with the test should be brought to bear on the decision" (p. 71). The standards specifically mention that "opportunity to learn" is a variable that may need to be considered in educational settings as it can seriously affect students' academic performance and "the validity of test score interpretations" (p. 72), and that neglecting this factor may result in "misdiagnoses, inappropriate placements and/or services, and unintended negative consequences" (p. 71). As a result, even though our analysis admittedly shows that contextualized measures of high school performance generally display slightly smaller effect sizes than their raw counterparts in their relationship to college success, we need to keep in mind that admission credentials should not be defined solely on the strength of its correlation to college performance. Instead, admission officers should consider students' learning opportunities and measures to assess their achievement in the context of their high school environments. Contextualized assessment has the potential to evaluate students' academic achievement in a more equitable and appropriate way and help expand college access to a broader, more diverse population of engineering students with the potential to succeed in college.

That being said, it is still noteworthy that we also found cases where contextualized measures displayed an even larger effect size than raw measures. This bolsters our argument that using not only raw measures of high school GPA but also their contextualized form, which incorporates contextual information that raw measures do not take into account, may be useful in identifying students with academic potential as well as pursuing equity in admissions. For instance, contextualized high school GPA displays a larger effect size in relation to four-year college graduation within engineering than does raw high school GPA at about half the institutions in our sample. Estimates from our split sample analysis also suggest that not only are contextualized measures of high school performance consistently related to college success for all three traditionally underrepresented student groups, there are some cases where contextualized measures have larger effect sizes, and thus display a stronger relationship with college success outcomes for underrepresented students than for the full sample of engineering students. For instance, as we mentioned in the results section, for female engineering students, contextualized ACT composite scores have a larger effect size in relation to first-year college GPA, than the effect size of the corresponding estimates for the full engineering sample. This suggests using contextualized ACT scores when making admissions decisions may be particularly useful for identifying women who are likely to succeed in four-year engineering programs, particularly as raw ACT scores consistently underpredict the achievement of college women [49]. Our findings also inform recent interventions to use more contextualized measures in college admissions, such as Landscape, which has been found to significantly increase the proportion of students admitted from underrepresented high schools and neighborhoods [50, 51].

Our findings also provide insights into how to use high school curriculum rigor in engineering admissions. High schools with comparatively fewer resources – in which low-SES, underrepresented students of color are disproportionately concentrated – are limited in the number of advanced STEM-related courses they provide [52]. Factors such as these disadvantage such students in admissions [3, 52]. Yet our results show that contextualized measures of curriculum rigor – which indicate how far a student progressed in math and science courses offered by their high school – show similar levels of significance and comparable effect sizes to raw measures of course rigor, in terms of their relationship with college GPA. Moreover, both raw and contextualized measures of high school course rigor display a weaker relationship with college GPA than do other measures of high school performance such as high school GPA and standardized test scores. In fact, high school science curriculum rigor shows the smallest effect size in its relationship with first-year college GPA among all measures of high school performance we tested in this study; this relationship is also not statistically significant in some of our sample institutions. This raises the possibility that institutions may benefit by evaluating students' high school course backgrounds in context of the course offerings that had been available to the student, and thus placing less emphasis on raw high school science course rigor when evaluating students in engineering admissions. Doing so may help remove unnecessary barriers for students coming from high schools with more expansive course offerings.

On a final note, although this paper focused solely on evaluating academic achievement in light of high school context, we also draw attention to the possibility that evaluating non-academic indicators within students' own respective contexts may also be a promising way to improve equity in admissions for underrepresented students in engineering. Recent studies show that extracurricular activities are yet another way for privileged students to distinguish themselves in college admissions [53, 54]. High schools with greater resources are able to provide students with not only quantitatively more extracurricular opportunities [54], but also qualitatively better extracurriculars [53]. Higher-resourced schools also tend to provide more tailored support, making it easier for students attending these schools to show distinction in a way valued by admissions officers [54]. Future studies may examine possible ways to contextualize extracurricular performance, and whether using these measures may help improve equity in admissions for underrepresented students in engineering.

6. Conclusions

Based on data from a Midwestern state's Department of Education, our analysis shows that both raw and contextualized measures of high school performance have strong, statistically significant relationships with engineering students' college success. In particular, among all the raw and contextualized measures of high school performance we examined, high school GPA appears to have the most consistent, strongest relationship with first-year college GPA, first-year retention, and four-year graduation within engineering. The strength of the relationship between measures of high school GPA and various indicators of college success has important implications for institutions going test-optional or test-blind, the number of which has been increasing enormously since the COVID-19 pandemic. Contextualized high school grades may be particularly helpful in conducting a holistic review of applicants in engineering programs that are implementing test-optional and test-blind admissions.

Our findings demonstrate the meaningfulness and effectiveness of incorporating contextualized measures into admissions to identify students with academic potential as well as pursue equity in engineering admissions. Our split sample analysis further provides supportive evidence for using contextualized measures to identify underrepresented student populations (women, underrepresented students of color, and low-income students) who are likely to succeed in engineering programs, narrowing the enrollment gaps between these student populations and their more privileged counterparts in engineering majors.

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