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Critical GPA and Standardized Test Score Admission Thresholds

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Abstract: We must increasingly engage and capitalize on the contributions of people from backgrounds underrepresented in engineering, especially women and people of color, if we are to educate enough engineers to meet demand and propel our nation's competitiveness through an engineering workforce reflective of our nation's diversity. This study focuses on broadening pathways into engineering, expanding both the diversity and size of the engineering student population. We hypothesized that engineering colleges' over-reliance on standardized test scores in the admission process inadvertently denies admission to diverse students capable of becoming successful engineers. Using the Multiple-Institution Database for Investigating Engineering Longitudinal Development (MIDFIELD) database of 226,221 engineering students, an investigation of whether admission data supports using a singular combined threshold using both high school grade point average and standardized test scores, or whether the data suggests using another model for predicting success in engineering as measured by a six-year engineering graduation rate. Of the predictive models that spanned all 11 institutions, high school grade point average was the most influential in predicting six-year engineering graduation. The next influential variable in predicting six-year engineering graduation was the higher education institution or ethnicity—a finding that suggests that the best predictive admissions model is specific to an individual institution, not an across-institutional model. Standardized test score was the most significant predictor in only one of the 11 institutions when modeled separately and in three others after high school grade point average. In seven of the 11 institutions, test score was not found to be a significant predictor of six-year engineering graduation for underrepresented minority students. A better understanding of the admissions profile of each institution might help determine what other factors are at play. Other potential factors that come to mind are financial aid, first-generation college-attendance and socioeconomic status.

Research Question: Is there a critical threshold (minimum) for high school grade point average and standardized test score(s) that accurately predicts underrepresented minority student success, defined as six-year graduation, in engineering? Does the threshold vary by higher education institution? We investigated whether the data supports using a singular combined threshold using both high school grade point average (HSGPA) and standardized test scores, or whether the data suggests using another model for predicting success in engineering as measured by a six-year engineering graduation rate.

Background: During 2005-2015, 81% of all U.S. undergraduate engineering degrees were awarded to men, and 80% to Caucasian and Asian Americans while, according to the U.S. Census, they only represented 51% and 62% of the total college-aged population in 2010 [1, 2]. Many of the programs—typically created between 1970 and 2000—that work at attracting more diverse students into engineering and increasing student persistence to graduation are minority enginering programs (MEPs) and women in engineering programs (WIEPs). Summer bridge programs are another widely disseminated approach to increasing student retention and persistence. Even with the support of these programs, the percentage of engineering bachelor's degrees earned by women in 2014 was 19.9%, just slightly above the 19.5% in 2005 a decade earlier. Students of color have historically been underrepresented in engineering and continue to be represented much lower than at parity in the population. Hispanic students earned 10.1% of U.S. bachelor's degrees in engineering in 2014, yet represented 20.7% of the U.S. college-aged population; Black or African American earned 3.5% (versus 14.8% in population), American

Indian 0.4% (versus 0.9%), Hawaiian/Pacific Islander 0.3% (not disaggregated) and Two or More Races 1.9% (versus 2.4%) [1], all much lower than in the U.S. population [2].

Despite all this programmatic focus on increasing the representation of women and minorities in engineering during the last few decades, no single solution has been identified, and is probably not realistic. But a systems approach, including changes in policy and practice, should be possible. Thus, a thorough understanding of the current climate of engineering admissions policy and practice is required.

Preliminary Findings—The variables selected in this investigation were chosen as the result of preliminary survey findings. In August 2013, an online survey was sent to admissions decision-makers at U.S. "high research-active" universities with engineering programs [3]. The survey contained 16 questions about specific engineering admission practices and policies, soliciting both rating and ranking of variables used in engineering admission decisions. Respondents were also asked about their roles and responsibilities in the engineering admission process to ensure responses were from decision-makers.

Survey results showed that a variety of factors are used to determine engineering admission eligibility. But—unsurprisingly—when asked to rate the importance of variables in the admissions process, the ubiquitous key factors for at least 74% of the respondents were high school grade point average; math and comprehensive standardized test scores; physics, calculus and chemistry high school track record; and the quality of the high school course load.

Next, respondents were asked to further differentiate amongst their top variables by ranking their "extremely important" variables *in order of importance*. The four variables ranked highest most frequently were: high school grade point average, math standardized test score, comprehensive standardized test score, and the quality of the high school course load. Notably, students' track records in calculus, physics and chemistry were ranked a bit lower than the overall quality of the high school course load. And, it is noteworthy that standardized test scores were prioritized as two of the top three admissions variables. Thus, the rationale for using high school grade point averages and standardized test scores.

Another survey question inquiring about median admission criteria found an ACT median math range of 23-34 among responding institutions, with an average of 29.5—a level only achieved by 6% of all U.S. ACT test takers in 2013 [4]. Likewise, the SAT Math score of 689 indicated as the average median score among survey respondents was achieved by only 8% of all SAT test takers in 2013 [5]. These results suggest the math standardized test score is a significant gatekeeper for access to engineering education, already narrowing the pool of "qualified" future engineers to far less than 10% of all test takers.

The high school grade point average and standardized test scores needed for admission to our engineering college continue to creep up year after year. Entering class 25th and 75th percentile standardized test score metrics and the percentage of students that were in the top quartile of their high school classes can be used as proxies for what is necessary for admission at a particular institution. For the 10 years between 2005-2014, at the ~200 institutions that provided the information to the American Society for Engineering Education, the percentage of students in the top quartile of their high school classes has hovered around 69% [1]. However, the standardized test score 25th and 75th percentiles have increased at these institutions, as shown in Table 1. The 25th percentile ACT score averages have increased more, 2.5 and 2.6 points, which is more than the 0.7 and 1.2 point increases for the 75th percentile average ACT scores [1].

Table 1. Engineering colleges' entry class metrics over a decade.

Year	Percent in Top Quartile HS class	Avg ACT Math 75%ile	Avg ACT Math 25%ile	Avg ACT Comp 75%ile	Avg ACT Comp 25%ile
2005	66.4	29.7	22.9	28.6	22.5
2006	68.5	29.7	23.4	28.7	23.2
2007	68.7	29.4	23.8	28.6	23.1
2008	68.5	29.9	24.0	29.0	23.5
2009	69.0	30.2	24.0	29.3	23.5
2010	70.0	30.2	24.6	29.4	24.0
2011	69.5	30.5	25.0	29.6	24.4
2012	69.6	30.5	25.1	29.6	24.5
2013	69.2	30.3	25.5	29.6	24.8
2014	68.6	30.4	25.5	29.8	25.0

These test score increases could be related to many factors that may not even be the same at each institution. At our own institution, increases were related to the growth in demand for engineering education and increases in the profile of students applying to our institution. Another related factor could be the impact institutions believe their entry class metrics and percentage of declined students play into their national rankings and selectivity categorization.

Table 2 displays the entry class metrics for students at various types of engineering institutions for the fall 2012 entry cohort at all engineering colleges across the U.S. that provided their data to the American Society for Engineering Education [1]. These specific entry metrics, which can be used as a proxy for admission requirements, are lower for Historically Black Colleges and Universities and Hispanic Serving Institutions than for other engineering colleges (for the ACT Math 25th percentile, Wilcoxon-Mann-Whitney HBCU vs. All, p=0.007, HSI vs. All, p=0.000, the difference in the two medians is significant and could not have come from a single population with the same median value). It is interesting to note that the ACT Math 25th and 75th percentile values are maxed out at a score of 36 in at least one of the engineering colleges. This means that the vast majority of the students at that institution had perfect ACT Math scores.

Table 2. Engineering entry class metrics for the 2012 cohort by institution type.

Institution Type		ACT Math 25%ile	ACT Math 75%ile	SAT Math 25%ile	SAT Math 75%ile	Percent Top Quartile HS class
HBCU (N=6)	Minimum	16	23	420	555	42
	Median	20	26	483	630	64
	Maximum	26	30	600	770	80
HSI or >30% Hispanic (N=12)	Minimum	11	26	200	570	21
	Median	22	28	535	650	59
	Maximum	25	36	570	800	100
All U.S. Engineering (198-205)	Minimum	9	14	200	520	11
	Median	25	30	600	695	70
	Maximum	36	36	760	800	100

Methods

For this investigation, the Multiple-Institution Database for Investigating Engineering Longitudinal Development (MIDFIELD) [6] data was used, and all the standardized test scores were converted to SAT values using the pre-2005 version of the ACT-to-SAT concordance table [7]. In the MIDFIELD database, the only ACT score variable provided is ACT Composite; therefore, all SATs were also converted to a total score—with a maximum of 1600 (sum of SAT Verbal and SAT Math, MIDFIELD data timeframe before SAT switched to separate Critical Reading and Writing scores with a maximum of 2400). For students with two SAT values after the conversion, the higher score was used.

Next, all high school grade point averages were converted to a 5.0 scale. Only five of the 11 institutions had maximum high school grade point averages less than 5.0; thus, converting to a 5.0 scale conserved data resolution among the six institutions using the wider 5.0 scale. It is not clear how each institution tracked the high school grade point average initially; a 4.0 at one school might be comparable to either a 5.0 or a 4.0 at another. Unfortunately, this is a limitation of the MIDFIELD dataset. For example, at one institution, a student who attended a high school that offered AP, advanced or honors courses that were graded on a 5.0 scale could have an average grade point higher than 4.0. As an example, let's assume a student earned As in every one of his or her courses, including those weighted on the 5.0 scale. That high school grade point average could be quite a bit higher than 4.0, however, in the student database it is input as a maximum of 4.0. Assume another student at the same school took the exact same course load and earned Bs in every weighted course. This second student could still earn a 4.0 and would appear the same in that system. Yet a third student who attended a school with no 5.0-weighted courses could also get a 4.0 grade point average if s/he earned all As across his/her transcript. Each of these three students might have had different experiences and outcomes from the courses they took, however, in the system, in which a 4.0 is the GPA maximum, they would appear the same. Other institutions use a different approach for tracking high school grade point averages, using the maximum value the high school reports on the student transcript. Unfortunately, we do not know the method used at each of the 11 MIDFIELD institutions; however, the two data changes allow comparison across and within all 11 institutions with the same variable and variable scales.

For this investigation, the dataset includes 89,296 students from 11 institutions, including two Historically Black Colleges/Universities. The breakdown of students in the dataset by race and ethnicity is 79% White, 8% Black/African American, 6% Asian, 3% Hispanic and 0.4% Native American. The dataset also has 1.5% international students and 1.1% other/unknown race or ethnicity. This represents 7,456 Black/African American, 2,635 Hispanic and 320 Native American students, for a total of 10,411 underrepresented minority students. Table 3 shows the engineering six-year graduation rates by race and ethnicity at each of the 11 MIDFIELD institutions; Table 4 shows the high school grade point average minimums, overall averages, average for URM students and maximum GPA at each institution. In the tables, the fields without data represent counts of 10 or fewer students, which was deemed too few to calculate a graduation rate by group.

Table 3. Engineering six-year graduation rates by race and ethnicity by institution.

Institution	Overall	Black or African American	Hispanic or Latino	Native American
1	43%	34%	38%	29%
2	36%	36%		
3	28%	27%	22%	25%
4	59%	51%	60%	67%
5	28%	32%		
6	49%	34%	57%	33%
7	56%	45%	52%	39%
8	39%	37%	35%	
9	55%	47%	46%	38%
10	42%	26%	44%	53%
11	42%	27%	36%	53%
Total	48%	35%	46%	39%

Table 4. High school grade point averages by institution (on a five-point scale).

Institution	Minimum HSGPA	URM Average HSGPA	Non-URM Average HSGPA	p-value	Max HSGPA
1	1.36	3.14	3.31*	0.000	5.00
2	1.00	3.60	3.44	0.399	5.00
3	1.00	3.48	3.79*	0.000	5.00
4	2.09	4.40	4.53*	0.000	5.00
5	1.10	3.08	3.08	0.933	5.00
6	1.82	3.46	3.67*	0.000	5.00
7	1.25	4.12	4.27*	0.000	5.00
8	1.82	3.36	3.44	0.125	5.00
9	1.73	4.39	4.50*	0.000	5.00
10	1.00	3.39	3.83*	0.000	5.00
11	1.63	4.29	4.45*	0.000	5.00
Total	1.00	3.70	4.10*	0.000	5.00

** Indicates significant difference between URM average HSGPA and Non-URM HSGPA within the institution or across all institutions. Significant differences in HSGPA between institutions was also found.*

Overview of Analysis Plan

Creating a six-year predictive graduation algorithm was investigated by generating sequential analyses—strategically adding and filtering out selected independent variables at each step. Models were created based on Exhaustive CHAID, CRT and QUEST algorithms (details below). The goal was to ascertain whether common thresholds of high school grade point average and standardized test score values exist across the various institutions that could predict engineering graduation success for underrepresented minority students.

Underrepresented Minority Categorization

We undertook creating a predictive algorithm to calculate the probability of an *individual* underrepresented minority student graduating from engineering in six (or fewer) years. For the data analysis to create such a predictive model, an initial category of “underrepresented minority” (URM) was created using a societal definition of underrepresentation in engineering based on race/ethnicity that included Black/African American (B), Hispanic (H) and Native American (I). During the initial iteration of trees (method explained below), it appeared that the predictive ability of the variables to detect differences in engineering graduation rates among students from various racial/cultural backgrounds was masked by the created URM category. In particular, analysis found that the two Historically Black College/Universities (HBCUs) kept both appearing and being grouped together, and being separate from other institutions. Thinking differently about the institution-specific cultural situations at the two HBCUs, we investigated to see if the admissions predictive model would be improved if a new URM2 category was created that took an institution’s dominant racial/ethnic population into consideration. Subsequently, at the two HBCU institutions, Black/African American students (greater than 80% of population at each) were *not* considered *underrepresented* (URM)—but all other ethnic and racial groups were within the new URM2 category including White and Asian American. This changed the total number of URM students being investigated from 10,411 to 8,664. While this approach does not conform to the widely used definition of underrepresented minority, it was postulated that Black/African American students experienced dominant (or majority) representation *within* the HBCU institutions that may be orthogonal to what URM students typically experience in White majority institutions. Following that logic, we explored to see if a more robust predictive admissions model might result. Implications for this change in perspective and data aggregation will be discussed further. This group is 31% female, 64% Black or African American, 30% Hispanic or Latino, 4% Native American, 1.2% White, 0.1% Asian and 0.3% International.

T-Test HSGPA and Higher Test Score by URM2

Before creating any models, the first analysis performed was a t-test for HSGPA and Highest Test Score by the re-categorized URM2 groups (Table 5). We found sufficient statistical evidence to infer that the mean HSGPA of 4.09 for non-URM students was higher than the mean of 3.76 for URM2 students. In addition, we could infer that the Highest SAT Total test score mean of 1226 for (80,632) non-URM students was greater than the mean of 1117 for the (8,664) URM2 students in this dataset. Recall that the 80,632 students that are not URM2 includes Asian, International, White and Other or Unknown for the nine predominately majority-serving institutions and also Black or African American students from the two HBCUs. These findings supported that we would be justified in looking for a different model of HSGPA and Highest Test Score for URM2 students.

Table 5. T-test for URM2 HSGPA and standardized test score.

Group Statistics						
	URM2	N	Mean	Standard Deviation	Standard Error Mean	Sig (2-tailed)
HSGPA 5.0	N	80632	4.0865	.69260	.00244	0.000
	Y	8664	3.7565	.79817	.00858	
Highest Test Score	N	80632	1225.62	143.052	.504	0.000
	Y	8664	1117.37	155.874	1.675	

Exhaustive CHAID

The Exhaustive CHAID (CHi-squared Automatic Interaction Detection) method, originally proposed by Biggs et al. [8], was performed iteratively using SPSS 23 to determine which predictor variables to use as well as to help define various threshold values. The dependent or target variable for this analysis was the binary (yes/no) engineering six-year graduation outcome. The predictor variables investigated were high school grade point average (converted to a 5.0 scale), highest SAT Total test score value (either converted from ACT Composite or original SAT Total), institution, ethnicity (using the same categories as the previous MIDFIELD investigation, A, B, H, I, N, W, and X), gender, and whether their ethnicity is categorized as underrepresented.

Exhaustive CHAID consists of three recurrent steps: merging, splitting and stopping.

Merging. The merging step uses an exhaustive search procedure that merges two categories iteratively, merging similar pairs until only a single pair remains. During our merging, each non-significant predictor variable category was merged, and the adjusted p-value was created. The Bonferroni adjustment uses a multiplier that is the sum of the number of possible ways of merging two categories at each iteration, with a maximum of 10 intervals. The p-values are calculated based on the data type of the dependent variable; if it is nominal, as is the case in this investigation, the null hypothesis of independence using observed frequencies to calculate Pearson chi-squared is used. Each final category after merging results in a child node on the tree. In our investigation, a child node includes predictor variable groups that have statistically similar graduation rates to each other but is different than all other child node groups in that level of the tree. The Chi-Square Pearson converge value of 0.001 was used with 100 maximum iterations.

Splitting. In the next step of Exhaustive CHAID analysis—splitting—the predictor variable with the smallest adjusted p-value is split into child nodes. If no predictor variable has a p-value less than or equal to the defined alpha-level, the node is considered a terminal node. We used an alpha-level of 0.05.

Stopping. Next, in the stopping step the software checks to see if the growing tree should be stopped based on various user-specified parameters or if the node becomes pure, which means it has identical values for each predictor variable. We indicated minimum parent nodes sizes of 100 individuals and minimum child node sizes of 50. Of note, these minimum node sizes could limit tree creation and identification of differences for groups with small numbers, such as Native American students. This iterative process of merging, splitting and stopping is repeated until the tree growth is fully stopped [8, 9].

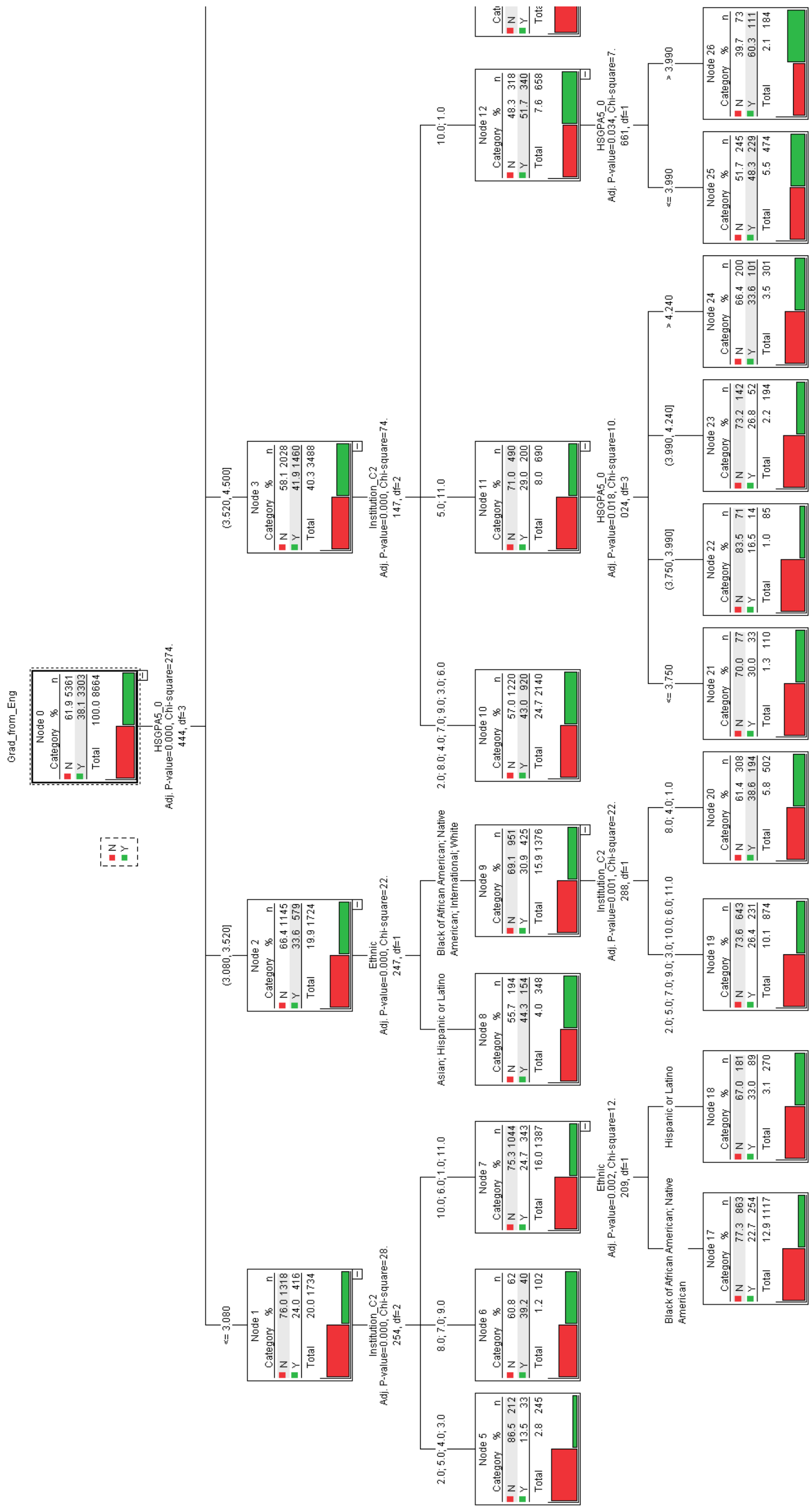
CRT (Classification and Regression Trees) and QUEST (Quick, Unbiased, Efficient, Statistical Tree) were also created using the same variables and settings to see which would create the best predictive model. The biggest differences between Exhaustive CHAID and CRT/QUEST is that CRT and QUEST are algorithms that produce binary trees that use univariate splits creating two (and no more than two) child nodes repeatedly. These models were compared to the Exhaustive CHAID models as explained below.

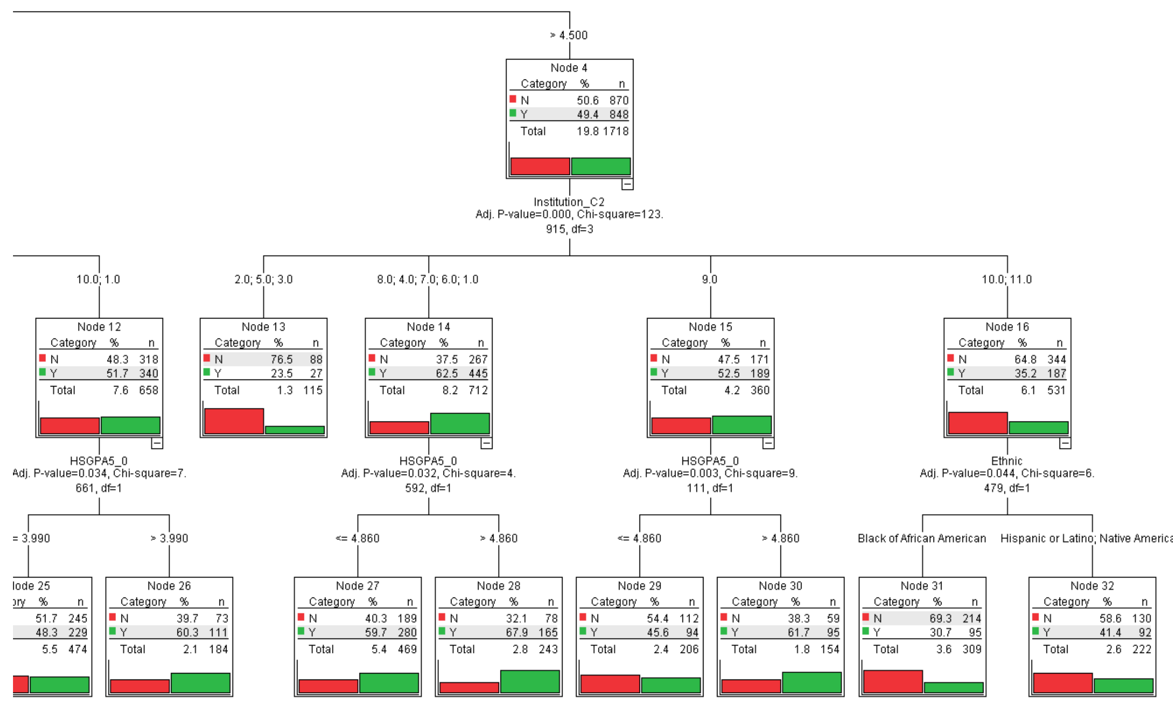
After various tree models are created, the predicted and observed classifications are considered to see how well the model has predicted the observed outcome. The overall percentage the model predicted correctly is compared across the various models to determine the best. As a result of the iterative process of creating trees from Exhaustive CHAID, CRT and QUEST, the predictor variables are included in a linear regression model.

Results

Of all the created predictive models that spanned all 11 institutions, the HSGPA converted to the 5.0 scale was the most influential in predicting six-year engineering graduation. The next influential variable in predicting six-year engineering graduation was the higher education institution or ethnicity, both for URM2 and non-URM students—a finding that disappointingly suggests that the best predictive admissions model is specific to an individual institution, not an across-institutional model that we had hoped could be developed from the 11-school MIDFIELD dataset. The example tree provided in Figure 1 shows the breakdown for URM2 students; this information is also summarized in Table 6.

Figure 1. Exhaustive CHAID tree for URM2 students, continued on next page.





> 4.500
Node 4
Category % n
N 50.6 870
Y 49.4 848
Total 19.8 1718
Institution_C2
Adj. P-value=0.000, Chi-square=123.
915, df=3
10.0; 1.0
2.0; 5.0; 3.0
8.0; 4.0; 7.0; 6.0; 1.0
9.0
10.0; 11.0
Node 12
Category % n
N 48.3 318
Y 51.7 340
Total 7.6 658
Node 13
Category % n
N 76.5 88
Y 23.5 27
Total 1.3 115
Node 14
Category % n
N 37.5 267
Y 62.5 445
Total 8.2 712
Node 15
Category % n
N 47.5 171
Y 52.5 189
Total 4.2 360
Node 16
Category % n
N 64.8 344
Y 35.2 187
Total 6.1 531
HSGPA5_0
Adj. P-value=0.034, Chi-square=7.
661, df=1
HSGPA5_0
Adj. P-value=0.032, Chi-square=4.
592, df=1
HSGPA5_0
Adj. P-value=0.003, Chi-square=9.
111, df=1
Ethnic
Adj. P-value=0.044, Chi-square=6.
479, df=1
= 3.990
> 3.990
<= 4.860
> 4.860
<= 4.860
> 4.860
Black of African American
Hispanic or Latino; Native American
Node 25
Category % n
51.7 245
48.3 229
5.5 474
Node 26
Category % n
N 39.7 73
Y 60.3 111
Total 2.1 184
Node 27
Category % n
N 40.3 189
Y 59.7 280
Total 5.4 469
Node 28
Category % n
N 32.1 78
Y 67.9 165
Total 2.8 243
Node 29
Category % n
N 54.4 112
Y 45.6 94
Total 2.4 206
Node 30
Category % n
N 38.3 59
Y 61.7 95
Total 1.8 154
Node 31
Category % n
N 69.3 214
Y 30.7 95
Total 3.6 309
Node 32
Category % n
N 58.6 130
Y 41.4 92
Total 2.6 222

Table 6. Summary of 11 institution model for engineering six-year graduation rate of URM2.

Tree Level 1	HSGPA <=3.08 24%	HSGPA (3.08-3.52] 34%	HSGPA (3.52-4.50] 42%	HSGPA >4.5 49%
Tree Level 2	Institution 4 @ 14% 4 @ 25% 3 @ 39% R	Asian, Hisp 44% Black, NA, Intl, White 31% I	Institution 7 @ 43% 2 @ 29% G1 2 @ 52% G2	Institution 3 @ 24% 2 @ 35% R 5 @ 63% G1 1 @ 53% G2
Tree Level 3	R = Race/Ethnicity Hisp 33% Black NA 22.7%	I = Institution 8 @ 26% 3 @ 39%	G1 = HSGPA <=3.75 30% (3.75,3.99] 17% (3.99,4.24] 27% >4.24 34% G2 = HSGPA <=3.99 48% >3.99 60%	R = Race/Ethnicity Black 31% Hisp, NA 41% G1 = HSGPA <=4.86 60% >4.86 68% G2 = HSGPA <=4.86 46% >4.86 62%

This tree shows that for the 8,664 underrepresented minority students (URM2) included in the model, 38.1% (3303) graduated from engineering in six-years. The HSGPA converted to the 5.0 scale is the most influential in predicting this graduation outcome, with an adjusted p-value of 0.000, chi-square of 274.444 with 3 degrees of freedom. The HSGPA has four nodes corresponding to HSGPA ranges less than or equal to 3.08, greater than 3.08 to 3.52, greater than 3.52 to 4.50 and greater than 4.50 on the 5-point scale. Of note, all following tree models and subsequent tables use interval notation in which using a parenthesis means a value is not included and a bracketed value is included in the range.

For the URM2 students in the lower GPA range (less than or equal to 3.08), a significantly lower 24% six-year graduation rate exists, varying from 13.5% to 39.2% depending on higher education institution. And within four institutions, we see that Hispanic or Latino students graduated from engineering at a statistically higher rate of 33% versus 22.7% for their Black or African American and Native American peers at those same institutions. Looking at the HSGPA range of greater than 3.08 to 3.52, we find a graduation rate of 33.6% for this group (higher than the 24% graduation rate in the lower HSGPA group).

The next predictor variable for this group is ethnicity (versus institution in the previous, lower HSGPA group), in which institution is not a predictor variable for Asian and Hispanic or Latino students within this HSGPA range. It is also interesting to note that when institution is a predictor variable, the institutions grouped together within this HSGPA range are not the same as the institutions grouped together in the lower HSGPA range of less than 3.08.

For the remaining two HSGPA ranges greater than 3.52, we again see groupings by higher education institution but no consistent pattern emerges in which institutions are similar. For these ranges, we also see that within certain—but not all—higher education institutions, the HSGPAs are further broken down to create the best predictive model. Recall that gender was included as a potential predictor variable, but it never came out as a predictor of six-year engineering graduation for this group.

Using the model with the same dataset results in 57.3% correct prediction of the engineering six-year graduation outcome, with 74.9% correctly predicting those that did graduate and 46.5% correctly predicting those that did not graduate—as shown in Table 7.

Table 7. URM2 Exhaustive CHAID model summary, risk and classification results.

Model Summary		
Specifications	Growing method	Exhaustive CHAID
	Dependent variable	Graduated from engineering
	Independent variables	HighestTestScore, HSGPA5.0, ethnicity, gender, institution
	Validation	None
	Maximum tree depth	3
	Minimum cases in parent node	100
	Minimum cases in child node	50
Results	Independent variables included	HSGPA5.0, institution, ethnicity
	Number of nodes	33
	Number of terminal nodes	21
	Depth	3

Risk	
Estimate	Std. Error
.522	.007

Classification			
	Predicted		
Observed	1 N	2 Y	Percent Correct
1 N	2491	2870	46.5%
2 Y	828	2475	74.9%
Overall Percentage	38.3%	61.7%	57.3%
Growing method: Exhaustive CHAID Dependent variable: Graduated from engineering			

The model for the typical definition of URM students only accurately predicts 27.1% of the observed URM students that graduated from engineering in six-years (not shown).

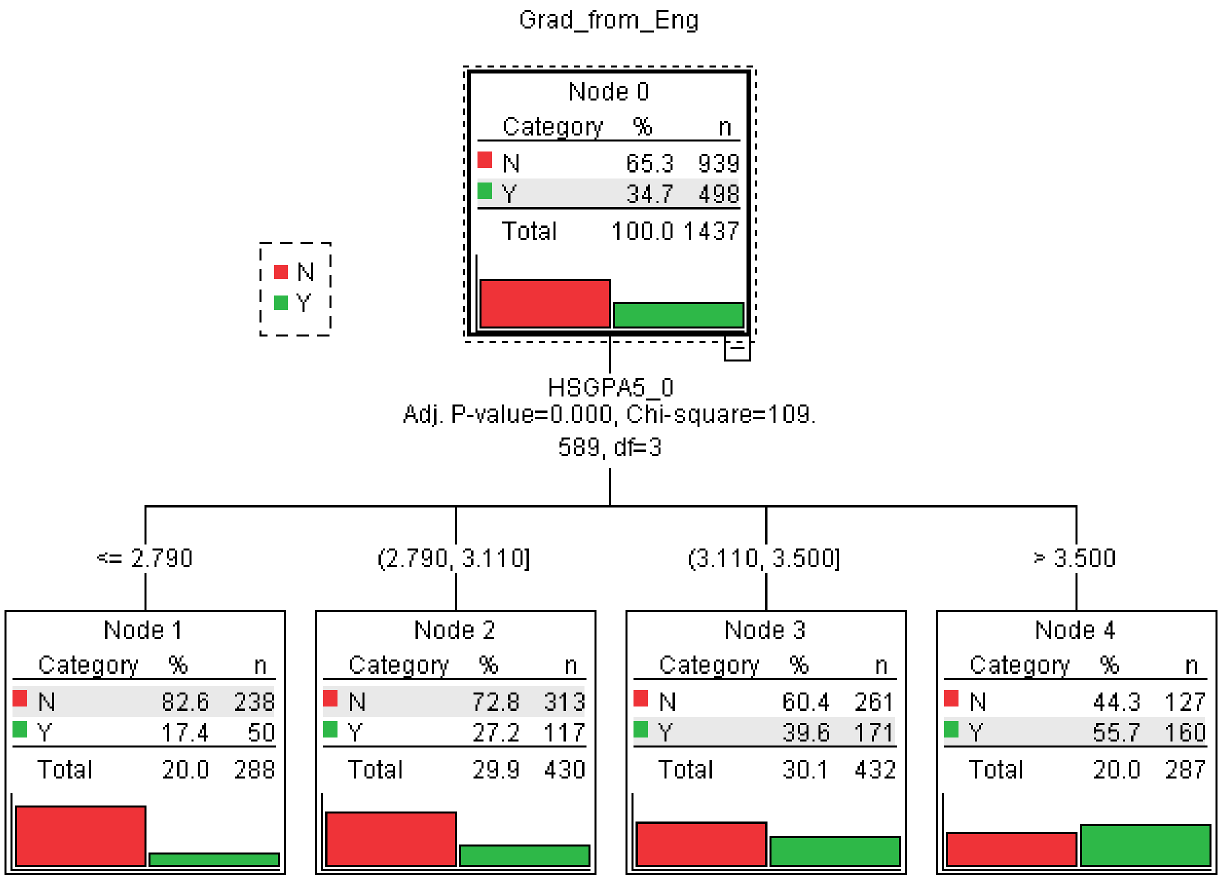
Next, individual institutions were investigated separately to see if those with similar outcomes could be grouped together. For this step, we went back to investigating all underrepresented minority students at the two HBCUs using the first definition. The same dependent (six-year gradation from engineering) and independent (standardized test score, HSGPA converted to the 5.0 scale, race or ethnicity, and gender) variables were investigated within institution. In eight of the 11 institutions, high school grade point average was found to be the most influential predictor variable. In one institution it was ethnicity, and in another it was standardized test score. And one institution did not result in any predictor variables from the independent variables included. Gender was not found to be a predictive factor in any of the 11 institutions for underrepresented minority students. It was found that at institutions where HSGPA was the most influential variable that predicted six-year engineering graduation, differences still existed in the category cutoffs for HSGPA, as shown in Table 8. Two examples of individual institution trees are shown in Figure 2 and Figure 3.

Table 8. HSGPA cutoffs by institution with associated engineering graduation rates.

Institution	Branch 1	Branch 2	Branch 3	Branch 4	Branch 5
1	<= 2.790 17.4%	(2.79, 3.11] 27.2%	(3.11, 3.50] 39.6%	> 3.50 55.7%	
2	<= 3.30 24.2%	(3.30, 3.98] 45.9%	(3.98, 4.37] 63.9%	(4.37, 4.97] 47.9%	> 4.97 24.6%
3	<= 2.97 11.9%	(2.97, 3.70] 28.0%	(3.70, 4.75] 48.9%	> 4.75 21.9%	
4	<= 4.31 42.4%	(4.31, 4.68] 51.8%	(4.68, 4.94] 64.7%	> 4.94 77.5%	
5	<= 2.97 19.6%	(2.97, 3.06] 37.1%	(3.06, 3.19] 19.0%	(3.19, 3.62] 39.0%	> 3.62 60.6%
6	<= 3.10 24.4%	(3.10, 3.68] 32.4%	(3.68, 3.99] 42.4%	> 3.99 58.5%	
7	<= 4.30 40.9%	> 4.30 58.3%			
8	N/A				
9	<= 4.45 41.7%	(4.45, 4.58] 26.9%	(4.58, 4.70] 41.0%	(4.70, 4.99] 53.8%	> 4.99 67.7%
10 – within test scores (920, 1180]	<= 3.40 27.8%	(3.40, 4.10] 48.5%	> 4.10 33.1%		
11 – for Black or African American	<= 4.00 20.2%	> 4.00 31.5%			
Model across All Institutions	<= 3.08 24.0%	(3.08, 3.52] 33.6%	(3.52, 4.50] 41.9%	> 4.50 49.4%	

Figure 2 includes the Exhaustive CHAID model with engineering six-year graduation outcome as the dependent variable, specifically filtered for only underrepresented minority students at institution 1. Node 0 shows that of the 1,437 underrepresented minority students within this institution, 498 (34.7%) graduated from engineering within six years. The remaining 939 (65.3%) did not graduate from engineering in that timeframe. For those 1,437 URM students, HSGPA is the best predictor of the graduation outcome from the variables being investigated (HSGPA, highest test score, gender and ethnicity) with an adjusted p-value of 0.000, chi-square of 109.589 and 3 degrees of freedom. For the 288 students with a HSGPA less than or equal to 2.79, the graduation rate drops to 17.4%. For the 430 students with a HSGPA greater than 2.79 but equal to or less than 3.11, we find a statistically higher graduation rate of 27.2%. For the 432 students with HSGPAs greater than 3.11 but equal to or less than 3.5, the graduation rate is 39.6%, and for students with HSGPAs higher than 3.50, the engineering graduation rate is 55.7%. Thus, using the predictive model for this institution only correctly predicts 61.4% overall.

Figure 2. Exhaustive CHAID tree model, risk and classification results for institution 1.

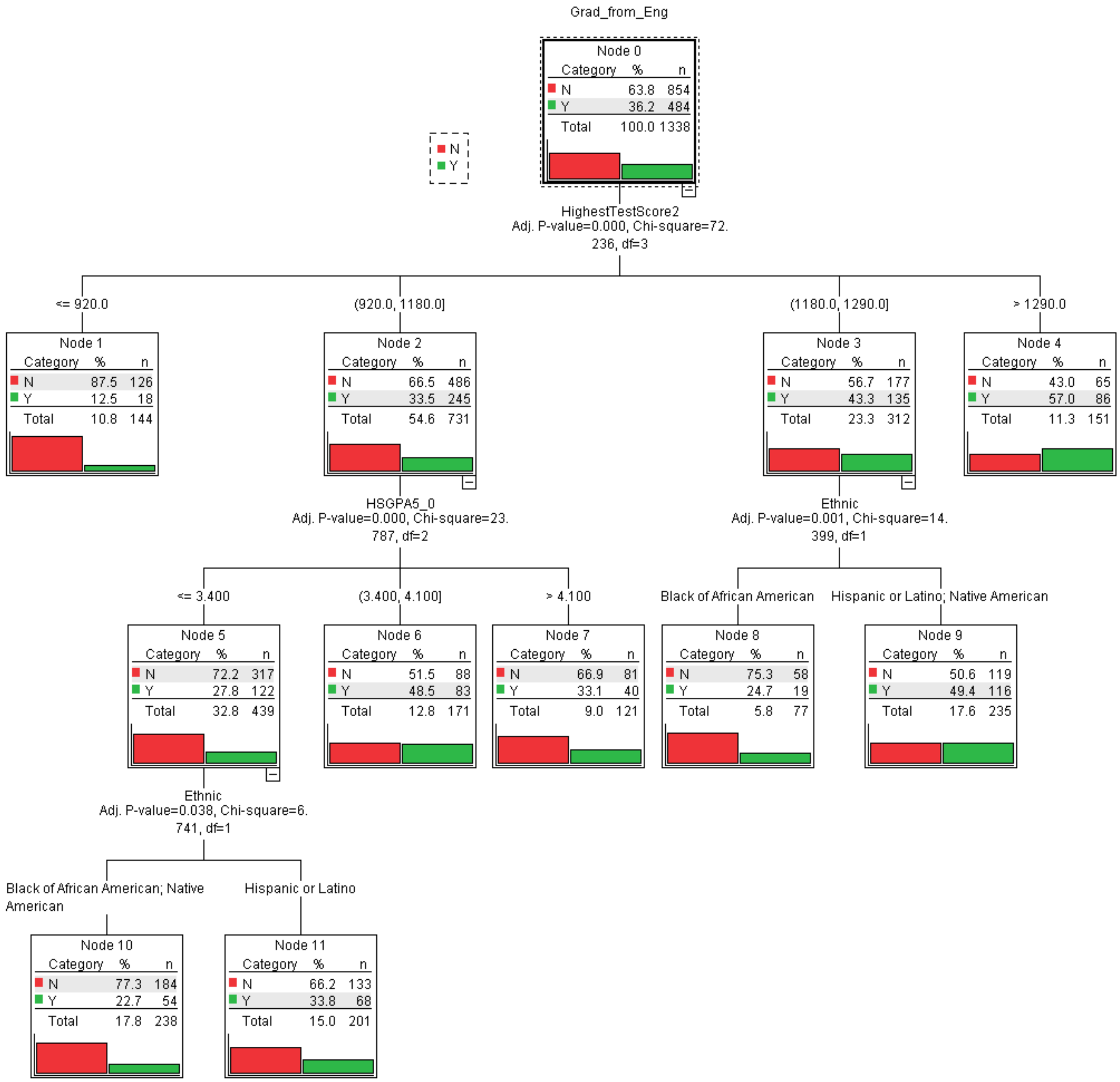


Risk	
Estimate	Std. Error
.502	.018

Classification			
	Predicted		
Observed	1 N	2 Y	Percent Correct
1 N	551	388	58.7%
2 Y	167	331	66.5%
Overall Percentage	50.0%	50.0%	61.4%

Institution 10 is unique because it is the only one at which the highest standardized test score came out as the *most* predictive of six-year engineering graduation outcomes, adjusted p-value 0.000, chi-square 72.236 with three degrees of freedom. As shown in Figure 3, 1,338 underrepresented minority students are included with 36.2% (484) graduating from engineering. Highest test score is split into four groups. Those with test score values of less than or equal to 920 (144 students) have an engineering graduation rate of 12.5%. Those with scores greater than 920 but equal to or less than 1,180 (731 students) have an engineering graduation rate of 33.5%, however, this node split further based on HSGPA. For the students in the test range (920, 1180] that also had HSGPA of 3.4 or less (439 students), the graduation rate was 27.8%. This node split again on the race/ethnicity variable with the 201 Hispanic or Latino students having a higher graduation rate of 33.8% and the 238 Black or African American and Native American students having a graduation rate of 22.7%. Moving back up and across the tree rather than down the current branch, the 171 students with HSGPA greater than 3.4 but less than or equal to 4.1 had a graduation rate of 48.5%. Oddly, the 121 students with the highest HSGPAs (greater than 4.1) within this test score range had a *lower* graduation rate, 33.1%, than the previous group. The 312 students with test scores greater than 1,180 but less than or equal to 1,290 had an engineering graduation rate of 43.3%. This node also split by race/ethnicity, with the 77 Black or African American students within this test score range having a 24.7% graduation rate and the 235 Hispanic or Latino and Native American students having a graduation rate of 49.4%. The highest test score range of greater than 1,290 had 151 underrepresented minority students included; they had a graduation rate of 57.0%. This model for institution 10 correctly predicts the six-year engineering graduation outcome of 59.9% overall. This second example contrasts the simple example of institution 1 and shows how different the models are for individual institutions, and how complex an overall model would be if one were to create a model for all institutions.

Figure 3. Exhaustive CHAID tree model, risk and classification results for institution 10.



Risk	
Estimate	Std. Error
.499	.018

Classification			
	Predicted		
Observed	1 N	2 Y	Percent Correct
1 N	449	405	52.6%
2 Y	131	353	72.9%
Overall Percentage	43.3%	56.7%	59.9%

Weighting for Prediction—Some of these models are not weighted in a way that makes the predicted outcomes favorable (i.e., the model for institution 7 predicts all students as graduating and does not predict any of the non-graduates), however, since the goal was not to create individual models for each institution, we moved to the next step instead of adjusting weighting on the individual models.

Adjusting HSGPA—Next, we investigated whether adjusting the HSGPA variable to account for the wide variation across institutions, using the HSGPA percentile within institution to compare across institutions, would allow grouping of those with similar trends in independent predictor variables. For example, institutions 1 and 3 both had HSGPA as their only predictor variable, but had differences in their HSGPA cutoffs for grouping.

While their 80^{th} percentiles for HSGPA were 3.50 and 4.79, the predicted graduation rates were 55.9% and 22.6%, not permitting the creation of a useful combined model because the graduation rates did not consistently increase with increasing HSGPA at both institutions. And, institution 3 had an *inverse* relationship; students with the top HSGPAs had the lowest engineering graduation rates. These results indicate that something else is going on that cannot be predicted with the MIDFIELD variables included in this research study.

Not about Test Score—When looking at the overall model across all institutions, the standardized test score was not found to be a significant predictor of engineering six-year graduation for underrepresented minority students (using the URM2 definition). However, standardized test score was found to be a significant predictor for non-underrepresented minority students and in the model created that included all students (after high school grade point average and institution). This in itself is interesting since standardized test scores are widely used in the admission decision process under the guise that they predict success for all students. This might infer that they predict success to graduation in engineering for the majority students who have historically populated engineering colleges, but not for underrepresented minority students, who increasingly populate engineering colleges as the nation’s youth population becomes more diverse.

Bottom Line—Standardized test score was the most significant predictor in only one of the 11 institutions when modeled separately and in three others after high school grade point average. In seven of the 11 institutions, test score was not found to be a significant predictor of six-year engineering graduation for underrepresented minority students.

Limitations—Only 11 institutions were included in the analysis, and while their sizes and diversity help make the results generalizable to engineering students at large public universities, the institutions are similar to each other in many ways. All the institutions are public, research universities with high or very high research activity, or are doctoral/research universities. None are small, private or liberal arts college settings. Of the 11 institutions, nine are in the South while one is in the West, one Midwest and none are in the North (using the regional university definition used by U.S. News and World Report). While these are limitations of the results, the types of institutions included in this study graduate the majority of the nation’s engineering bachelor’s degree recipients each year.

Another study limitation is that even when the historic data from the 11 MIDFIELD institutions were pooled together, the dataset still contained small numbers of URM students in some categories or at some institutions. These small population sizes may lack the power necessary to realize statistical differences, even when a meaningful difference may exist. About 20% of the

Black or African American students in the dataset were enrolled in two HBCUs that offer different surroundings than the majority-serving institutions, however, none of the schools studied were Hispanic Serving Institutions.

While this research focused on women and students from racial and ethnic backgrounds typically underrepresented in engineering, no focus was made on international or non-domestic students. Since this study concentrated on high school grade point averages and standardized test scores that are common in the U.S., many international students were filtered out because they lacked these variables in their admission records. In addition to the lack of consistent variables common to domestic students, a concern also exists about widespread cheating among students from certain countries or regions [10, 11, 12]; therefore, the engineering success of international students is best investigated separately.

Another limitation is that admission policies and practices may have varied through time even within institution. Related to this is high school grade point average inflation over time and grade non-equivalence [13]; this research did not investigate grade inflation; however, if grades uniformly inflate, we expect that HSGPA would still be a good predictor of engineering success until the vast majority of engineering-bound students have maximum grade point averages. However, high school grade inflation and changes in admission practices could impact the high school grade point average threshold values found for success to graduation in engineering.

Also, when students near the bottom of the test score or high school GPA ranges were admitted and enrolled at an institution, we do not know what other factors were considered or impacted their admission and enrollment decisions. Such unknown factors could play a major role in predicting success to graduation in engineering.

Further, the applicability of this research may be limited to institutions with limited or selective admissions criteria, and thus might have no application at “open admissions” or “open enrollment” institutions. The findings are also limited to undergraduate study.

Conclusion

In the predictive models created that spanned all 11 institutions, the HSGPA converted to the 5.0 scale was the most influential in predicting six-year engineering graduation; however, the next influential variable in predicting six-year engineering graduation was the higher education institution or ethnicity. This finding suggests that the best predictive admissions model would be specific to an individual institution, not an across-institutional model. While this answers the second part of the research question, it means that HSGPA and test score critical thresholds should not be modeled *across* institutions. When institutions with similar predictive models were considered for comparison, it was found that their differences made grouping them unreasonable.

Clearly, more is happening within institutions that cannot be modeled by the independent variables investigated in this research, and which drive admission to engineering (HSGPA, standardized test score, gender and ethnicity). A better understanding of the admissions profile of each institution might help determine what other factors are at play. Other potential factors that come to mind are financial aid, first-generation college-attendance and socioeconomic status.

References

[1] American Society for Engineering Education, Engineering College Profiles & Statistics Book, Washington, DC: ASEE, 1998-2015.

[2] U.S. Department of Commerce, "U.S. Census Bureau," 2010. [Online]. Available: http://www.census.gov.

[3] B. A. Myers and J. F. Sullivan, "Beginning to Quantify the Pool of Engineering-Eligible Prospective Students through a Survey of Access Practices," in *2014 ASEE Annual Conference*, Indianapolis, IN, 2014.

[4] ACT, Inc., "ACT Profile Report - National," ACT, Inc., Iowa City, IA, 2015.

[5] The College Board, "SAT Data Tables-Critical Reading, Mathematics and Writing Percentile Ranks by Gender and Ethnic Groups.," The College Board, New York, 2015.

[6] M. W. Ohland, G. Zhang, B. Thorndyke and T. Anderson, "The creation of the Multiple-Institution Database for Investigating Engineering Longitudinal Development (MIDFIELD)," Salt Lake City, UT, 2004.

[7] ACT and SAT, "ACT-SAT Concordance Study: June 2008," June 2008. [Online]. Available: http://www.act.org/aap/concordance/pdf/reference.pdf.

[8] D. Biggs, B. de Ville and E. Suen, "A method of choosing multiway partitions for classification and decision trees," *Journal of Applied Statistics*, vol. 18, pp. 49-62, 1991.

[9] IBM, "IBM Knowledge Center," 2013. [Online]. Available: http://www-01.ibm.com/support/knowledgecenter/SSLVMB_22.0.0/com.ibm.spss.statistics.algorithms/alg_tree-chaid.htm.

[10] E. Redden, "Inside Higher Ed," 9 July 2015. [Online]. Available: https://www.insidehighered.com/news/2015/07/09/admissions-process-broken-chinese-students.

[11] L. Krantz and J. Meyers, "Boston Globe," 19 January 2016. [Online]. Available: https://www.bostonglobe.com/metro/2016/01/19/chinese-students-hungry-attend-universities-caught-fraudulent-application-process/gpRB06mqBVAsxZ6eAbFKCJ/story.html.

[12] T.-P. Chen and A. Schultz, "The Wall Street Journal," 5 June 2015. [Online]. Available: http://www.wsj.com/articles/cheating-concerns-in-asia-cloud-sat-testing-1433549895.

[13] K. E. Godfrey, "Investigating Grade Inflation and Non-Equivalence," College Board, 2011-2.