A Comparative Analysis of Underrepresented Engineering Applicants Admission Practices and their Academic Performance at the University of Illinois at Chicago

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Dr. Darabi is an ABET IDEAL Scholar and has led the MIE Department ABET team in two successful accreditations (2008 and 2014) of Mechanical Engineering and Industrial Engineering programs. Dr. Darabi has been the lead developer of several educational software systems as well as the author of multiple educational reports and papers. Some of these products/reports have already been launched/completed and are now in use. Others are in their development stages. Dr. Darabi's research group uses Big Data, process mining, data mining, Operations Research, high performance computing, and visualization techniques to achieve its research and educational goals.

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Dr. Peter C Nelson, University of Illinois, Chicago

Peter Nelson was appointed Dean of the University of Illinois at Chicago's (UIC) College of Engineering in July of 2008. Prior to assuming his deanship, Professor Nelson was head of the UIC Department of Computer Science. In 1991, Professor Nelson founded UIC's Artificial Intelligence Laboratory, which specializes in applied intelligence systems projects in fields such as transportation, manufacturing,

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bioinformatics and e-mail spam countermeasures. Professor Nelson has published over 80 scientific peer reviewed papers and has been the principal investigator on over $30 million in research grants and contracts on issues of importance such as computer-enhanced transportation systems, manufacturing, design optimization and bioinformatics. These projects have been funded by organizations such as the National Institutes of Health, the National Science Foundation, the National Academy of Sciences, the U.S. Department of Transportation and Motorola. In 1994-95, his laboratory, sponsored by the Illinois Department of Transportation, developed the first real-time traffic congestion map on the World Wide Web, which now receives over 100 million hits per year. Professor Nelson is also currently serving as principal dean for the UIC Innovation Center, a collaborative effort between the UIC Colleges of Architecture, Design and the Arts; Business Administration; Medicine and Engineering.

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I am a Senior Data Scientist at Exelon Corporation. My area of expertise is to apply Machine Learning and Big Data Analytics methods in real life problems and drive efficient solutions by creating data products. Prior to joining Exelon, I was a PhD student in Industrial Engineering and Operations Research at the University of Illinois at Chicago. During my graduate studies I was involved in several data analytics projects in Healthcare and Education.

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A Comparative Analysis of Underrepresented Engineering Applicants Admission Practices and Their Academic Performances at the University of Illinois at Chicago

Abstract

Universities have been challenged with the task of creating admission standards to more fairly access underrepresented applicants. This paper illustrates a quantitative framework to measure and classify the underrepresentation level of feeder high schools to the College of Engineering (COE) at the University of Illinois at Chicago (UIC). It further proposes how such a framework may support the admission decisions. Our study is limited to students who were admitted to UIC as first time freshman. The data set includes the records of more than 3,000 students who entered the University as freshman between 2008 and 2013. Each student in the data set was assigned an Under Representation Score (URS), which was calculated based on the attributes of each student's high school. Our analysis included extensive data mining, where we chronologically traced each student's academic performance over their first four semesters. In addition to standard performance indices, such as retention and dropout rates, we also defined new performance indices that were fundamental in measuring the academic performance of underrepresented students. Our analysis proposed that by incorporating URS to the admission criteria, the COE might improve admission the process for underrepresented applicants. We also showed that, compared to the rest of the students, underrepresented students have higher dropout rates in their first three semesters. However, those underrepresented students who stay and finish their first three semesters, perform equally well, if not better, than the rest of the students. Based on this analysis, we have suggested a revised set of admission criteria. We have also underlined the importance of monitoring and special advising systems for underrepresented students.

I. Introduction

Problem Description

The objective of this paper is to measure how underrepresented students were admitted to the COE and how they performed academically in their first two years compared to the rest of the students. The other aspect of this paper is to identify and suggest action plans to increase the number of underrepresented students who enter the COE. The concrete research question of this study is: Can high school information for underrepresented students and their ACT scores be used to predict the student's academic performance? We hypothesize that, academic performance from underrepresented high schools cannot alone be used to predict the performance of a student.

A student's success is determined on motivational and personal characteristics[24]. Admitting a student based solely on the current criteria is not a good practice. In our study, an additional quantitative factor, URS, will be introduced to assist in admitting underrepresented students.

Figures 1 and 2 illustrate the relationship between ACT, College Readiness Index (CRI), and Total Economic Disadvantage (TED) for COE applicants from different feeder high schools between 2008 and 2013. The College Readiness Index and Economic Disadvantage factors of different feeder high schools were obtained from US News. The horizontal axis represents college readiness (in Figure 1) or economic disadvantage (in Figure 2). The left vertical axis in each figure is the average ACT for the corresponding college readiness or economic disadvantage. The right vertical axis in each figure is the number of applicants for that index. For example, as read from Figure 1, there were about 800 applicants from high schools with a College Readiness index of 94. The average ACT for this group was 27. From these figures, there is a visual understanding that as college readiness increases, average ACT increases and as economic disadvantage increases, average ACT decreases. We used the intuition illustrated by these figures in constructing a quantitative index for underrepresentation that will be discussed later in this paper. In the following, we review the related literature.

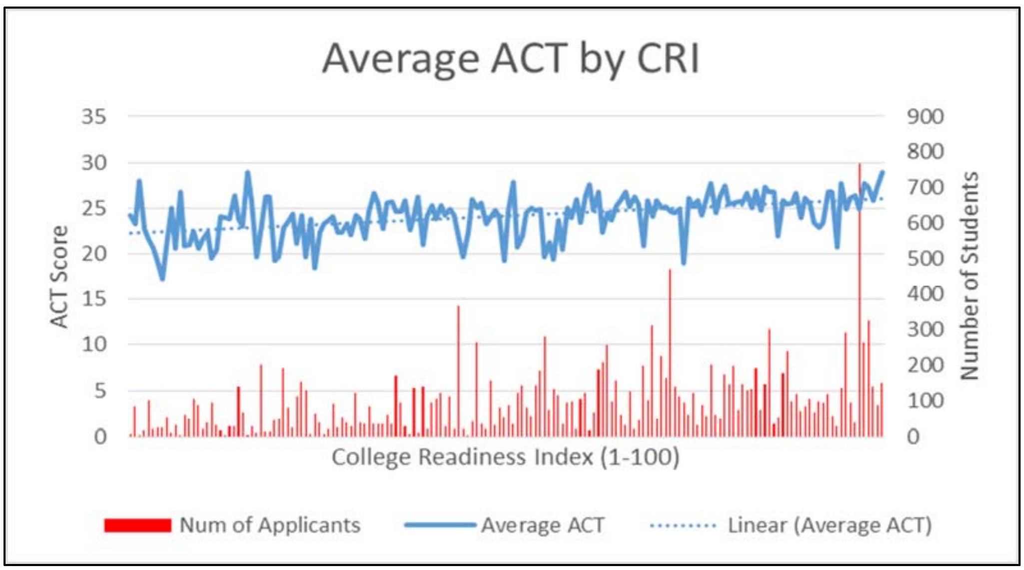

Figure 1: Illustrates the change in Average ACT as College Readiness increases from left to right and the number of Applications from each Index.

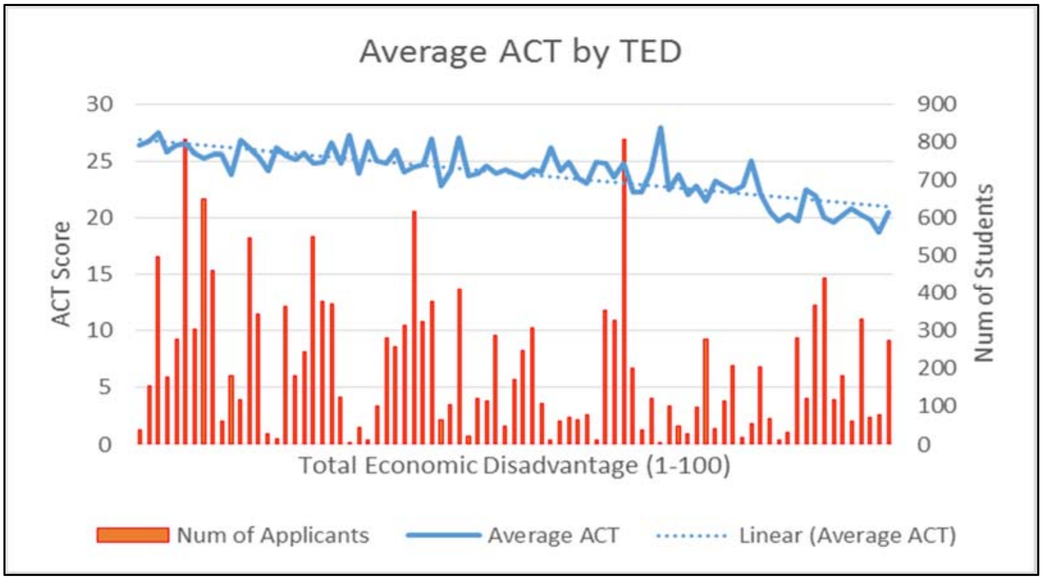

Figure 2: Illustrates the change in Average ACT as Total Economic Disadvantage increases from left to right and the number of Applications from each Index.

Motivation

Over the past several decades, the United States has been experiencing a rising need for qualified engineers. Engineers are necessary to a society when resolving problems that involve national security, healthcare, economy, and environment. Engineering occupations are projected to add 136,500 jobs over the next decade[18]. When considering how the United States can answer the demand for qualified engineers, two problems are apparent. First, there is need for a stronger engineering workforce, regardless of factors such as ethnicity or gender. Second, there is a lack of participation from under-represented ethnicities in the field of engineering.

Before describing how to address the issue of underrepresented participation, it is important to first understand why there is a need to focus on this group. At least three reasons underscore the need for doing so: Our sources for the future Science and Engineering (S&E) workforce are uncertain; the demographics of our domestic population are shifting dramatically; and diversity in S&E is a strength that benefits both diverse groups and the nation as a whole[16]. According the Bureau of Labor Statistics, for the year of 2014, the percentage of African Americans and Hispanics in architecture and engineering occupations are 5.2 and 8.2, respectively[1]. These percentages are not increasing as fast as average, based on the population of these ethnic groups in the United States. According to the 2014 United States Census, 13.2% of the United States population is African American[22].

In addition to providing a significant number of potential engineers, the diversity introduced by engineers hired from underrepresented population is itself a positive asset. *The Difference*, argues that diverse groups are typically smarter and stronger than homogeneous groups when innovation is a critical goal, as it is now in our globally competitive environment[17]. Daryl Smith concluded that diversity initiatives positively affect both minority and majority students on campus in terms of student attitudes toward racial issues, institutional satisfaction and academic growth[19].

Increasing the number of engineers from underrepresented populations has been a concern for several decades. For this reason, much research has been conducted to combat the problem at all levels of education. Our focus is on the way underrepresented students are admitted to the COE. The use of varying admissions standards, indicators, and support systems are becoming important tools of several educational researchers. Some of these research topics will be described in the following text.

Admission Methods

One such method is being used at the School of Dentistry at the University of Louisville (ULSD). ULSD has increased its pool of underrepresented minority applicants through three major methods: partnerships and collaborations, mentoring, and restructuring administration[15].

Another study conducted through Princeton University examines how elite universities are modifying the admissions of specific groups of applicants. The study analyzed the bump in admission standards for SAT scores using a logistic regression. The bonus for African-American applicants is roughly equivalent to an extra 230 SAT points[4].

A study out of the University of Oklahoma addressed the decreasing enrollment of engineering students across the nation. As a result, the school investigated the key factors that influence selection of engineering as a career path and initiated a corrective program to reverse this trend[2]. This study is not focused on how the applicants are admitted, but focused on recruiting applicants based on key factors.

Additionally, the U.S. Coast Guard Academy suggested two methods to achieve diversity. In model A, the strategy is to attract academically "qualified" minorities who have the desired standardized test scores, GPAs, and curriculum experiences in mathematics. In model B, the strategy is to recruit "educationally disadvantaged" students who have demonstrated the aptitude and attitude to succeed[25].

The term underrepresented encompasses a large number of categories of population. One such category is the female population. This is discussed in a paper written through Virginia Tech. Our study highlights three themes consistent across the institutions: 1) institutional commitment and self-awareness, 2) strategic admissions policies and "high touch" efforts, and 3) integrated outreach programs[10].

Another method to increase the number of underrepresented applicants was conducted through the University of Cincinnati. Their College of Engineering used a precollege Pathway Program focusing on the underrepresented population. The objective of the "Pathway Programs" is to increase the awareness and interest of underrepresented ethnic students in pursuing engineering as an academic major; and to assist in their math/science academic preparation[11].

These methods incorporate a wide variety of different solutions to the same problem. Our intention is to create a framework that can be used at the point of admission. This eliminates recruiting or pursuing students before application and only focusing on those who apply. Some methods suggested altering the ACT/SAT for underrepresented populations. However, their system uses factors that are dependent on race, which is not necessarily the determining factor for underrepresentation. Our focus is to increase the number of underrepresented students who have the potential to succeed regardless of race or gender.

Retention Strategies

When discussing admissions, it is necessary to consider the importance of retention. Our study does not suggest how to retain students but does stress the need for retention. Research indicates that programs designed to target first year students increase their likelihood of success during that year and their chances of completing an undergraduate education[12]. These concern issues of institutional action, program implementation, and the continuing challenge of promoting the success of low-income students[21]. Some methods on how to retain students follow.

A paper written through Michigan Tech addresses the use of mentors as a way to retain underrepresented students. The graduate, undergraduate initiative for development and enhancement (GUIDE) program creates a supportive environment for first year engineering students from underrepresented groups[9]. An additional study looked at the use of counseling services. The results indicated that counseling experience is significantly associated with student retention: students receiving counseling services were more likely to stay enrolled in school[13]. A third study analyzed the impact of integrating students into the research process on retention. Findings of a participant-control group design show that the research partnerships are most effective in promoting the retention of students at greater risk for college attrition African American students and students with low GPAs[8].

Another paper discussed the use of orientation courses to increase retention. This study was done through a community college. A chi-square analysis revealed a significant association among orientation program, student completion of degree, student retention, and student enrollment and persistence[3].

Student retention goes beyond the basics of academic scope. Studies have shown that non-academic factors must be considered when analyzing retention. The overall relationship to college retention was strongest when SES (Socioeconomic Status), GPA (High School Grade Point Average), and ACT Assessment scores were combined with institutional commitment, academic goals, social support, academic self-confidence, and social involvement[14]. Meaning that in order to find those students who require increased attention, we must look at their previous academic performance in addition to their economic status.

Prior to initial enrollment, undergraduates completed surveys assessing expectations about their college adjustment, and later completed a second survey assessing actual adjustment. Six years later inspection of academic transcripts revealed which students had dropped out and whether they had been in good academic standing or poor academic standing. Generally, emotional and social adjustment items predicted attrition as well or better than academic adjustment items[7].

Predictors of fall-to-spring and fall-to-fall retention for 9,200 first-time-in-college students enrolled in a community college over a four-year period have been analyzed in another study. Findings highlight the impact of developmental education programs and internet-based courses on student persistence. Additional predictors include financial aid, parents' education, the number of semester hours enrolled in and dropped during the first fall semester, and participation in the Student Support Services program[6].

In post-freshman year student surveys, dispositional and academic optimism, as well as better motivation and adjustment, have been found among the traits of successful students and associated with lower likelihood of dropping out. Academic optimism was also associated with higher grade point average GPA[20]. This allows universities to determine which students will need help in the following years. If a student does not match the successful factors, they should be offered some sort of assistance. Another study used a similar method in examining pre-enrollment variables as retention predictors. Additional risk is associated with the age range 20–24, attending part-time, and being an ethnic minority other than Asian[5]. The concern of retention has the ultimate goal of graduation, when referring to college education. To achieve a higher graduation rate at U.S. colleges and universities, it was suggested that there are financial tradeoffs between students dropping out of a college and the establishment of an effective student success program[23].

Our study will establish underrepresented students as a group of students that will likely need increased attention to maintain retention, and there exist additional methods that may accomplish such. Additionally, in the context of our study, the term ‘underrepresented’ refers to an individual that originates from a disadvantaged high school. Based on this definition, it can be seem that more disadvantaged high schools tend to have higher minority populations.

The remaining sections of this paper are as follows. A summary of the data used and its limitations will be addressed in the Data and Methodology section of the paper (Section II). In Section III, we introduce a new academic performance indicator, called Under Represented Score (URS). We conducted statistical analysis is conducted in the Validation section (Section IV), this will determine how students coming from underrepresented schools perform academically compared to the rest of the students. The Discussion section will address the average number of times courses are taken, race as a factor, and a framework for incorporating

URS into admission. We then draw conclusions, followed by our future work in Sections VI and VII, respectively.

II. Data and Methodology

Data Collection

The student dataset was obtained from our university's database. This dataset included records of over 3,000 students from the College of Engineering, along with other STEM majors (Biological Science and Chemistry) that require similar math and science courses in their first two years of study. The data for each student included composite ACT score, math ACT score, high school name, race, major, the term they were registered for courses, courses taken in college, and grades for each course taken.

The obtained data set was limited to students who meet the following criteria:

- Be a new first time freshmen.
- Start in the COE, Biological Science, Chemistry, or Psychology between 2008 and 2013.
- Be from a high school that its CRI and TED indexes are known.
- Be from a high school that feeds an average of at least one student per year to our university.

The student must be a freshmen for URS to be a factor in their admission, transfer students are admitted to our university based on different policies. Students must start between the given years so that our data is current but allows for them to progress through courses. The extent of information that can be gathered from U.S. News is limited, which limited the number of high schools in our study. Finally, the student must originate from a high school that consistently sends students to the specified majors.

III. Results

The URS was developed using information from the U.S. News database. Data for college readiness index (CRI), and total economic disadvantage (TED). CRI is scaled from 0-100 where the level of preparation for college increases as CRI increases. TED is scaled from 0-100 where the financial status gets worse as TED increases. Using this information a URS was developed for each high school and then applied to the students in our dataset. Equation 1 shows the function used to calculate the URSi, where i represents a high school in our study. Without loss of generality, we decided to put an equal weight on CRI and TED. We tried different combinations of weights for CRI and TED and the 50-50 percent combination was the best for the classification of our feeder high schools. These weights work well for our university because our students originate from high schools that span the full range (approximately 0-100) of the two variables. For other universities, different weight combinations may be more effective based on the situation of the university and its feeder high schools.

$$URS_i = \frac{100 - CRI_i + TED_i}{2} \tag{1}$$

After calculating the URS of each feeder high school, the high school was placed in one of the three different URS classes as shown in Table 1. Low Underrepresentation (LU) class contains high schools with high college readiness indices and low economic disadvantage. High Underrepresentation (HU) class contains high schools with low college readiness indices and high economic disadvantage. Moderate Underrepresentation (MU) class contains high schools with average college readiness indices and economic disadvantage. Table 1 also shows the number of high schools in each URS category as well as the number of students from those high schools.

Table 1: Breakdown of Classes by URS

Classes	URS Range	Num. of High Schools	Num. of Students
LU	0-30	15	355
MU	31-61	86	2,330
HU	62-100	62	889

The URS classes were developed based on two main criteria. *The **first criterion** was that for the population of the students who came from the high schools of a given class, there is no significant relationship between the average ACT and the dropout event of those students. The **second criterion** was that for each pair of classes, the class with a higher URS interval has a higher average dropout rates for its students.* We tried to find the minimum number of classes that satisfy the above two criteria to make sure each class is constructed based on a minimum number of students that allows valid statistical analysis. Every possible range of URS was studied for two and three classes. Table 1 shows the only range that satisfied the stated conditions.

If the above two criteria are satisfied, it can be argued that similar admission or retention strategies might be applied to all the applicants/students within a URS class. When comparing students of different URS classes, students from MU and HU may need the support of different admissions criteria and retention programs to succeed. We would like to point out that such classification techniques cannot completely determine which exact admission or retention strategy must be selected for each individual applicant/student. Such a decision can only be made by careful examination of the individual student's information and conditions. However, classification techniques discussed here can be used as a support tool for screening the applicants/students before carefully examining their information. The application of these techniques in some cases might prevent the rejection of some underrepresented applicants who are rejected if regular admission criteria are used. We discuss this topic in more details in Section V.

IV. Validation

First Criterion

To validate the first criterion for the URS classes in Table 1, we performed the hypothesis tests shown by Equation 2. Due to the large sample size, we assume our data has normal distribution as per the Central Limit Theorem. When analyzing student's previous academic achievements the variable ACT score is emphasized more in this paper due to the fact that it is a standardized test. High School GPA was not chosen, because high schools do not have a universal standard in calculating GPA. High schools in our study use both varying scales (typically 4.0 or 5.0) or offer Advanced Placement courses, which affects the student's high school GPA based on weighting.

$$H_0: \mu_{HS\ ACT\ of\ students\ that\ dropped\ out} = \mu_{HS\ ACT\ of\ students\ that\ did\ not\ drop\ out} \qquad (2)$$

$$H_1: \mu_{HS\ ACT\ of\ students\ that\ dropped\ out} \neq \mu_{HS\ ACT\ of\ students\ that\ did\ not\ drop\ out}$$

$$Testing\ with\ an\ \alpha\ level\ of\ 5\%$$

It is necessary to define what the term 'drop' means in the context of this study. A student is said to drop from the University if they do not complete the first four semesters and do not return within two semesters (excluding summer terms). We define a drop in such a way for three reasons. 1) The courses that are being analyzed in the following sections are typically taken in the first four semesters. 2) Our data contains students that started their education in 2013 and have yet to graduate. Therefore, graduation cannot be used as the threshold for success. 3) Students that complete their fourth semester have proven their academic abilities. Dropping after this point is more likely to be due to non-academic circumstances. The purpose of this criterion is to show that, within each class, there is no statistical dependence between ACT score and drop event.

The following figures illustrate the typical ACT within each class. Figure 3 shows the average ACT of students that drop out versus those who stay by URS class. Figure 4 conveys the same information as Figure 3 however, Figure 4 breaks down the information by race. This shows that the ACT is consistent by race within a class. Table 2 give the actual values listed shown in Figure 3.

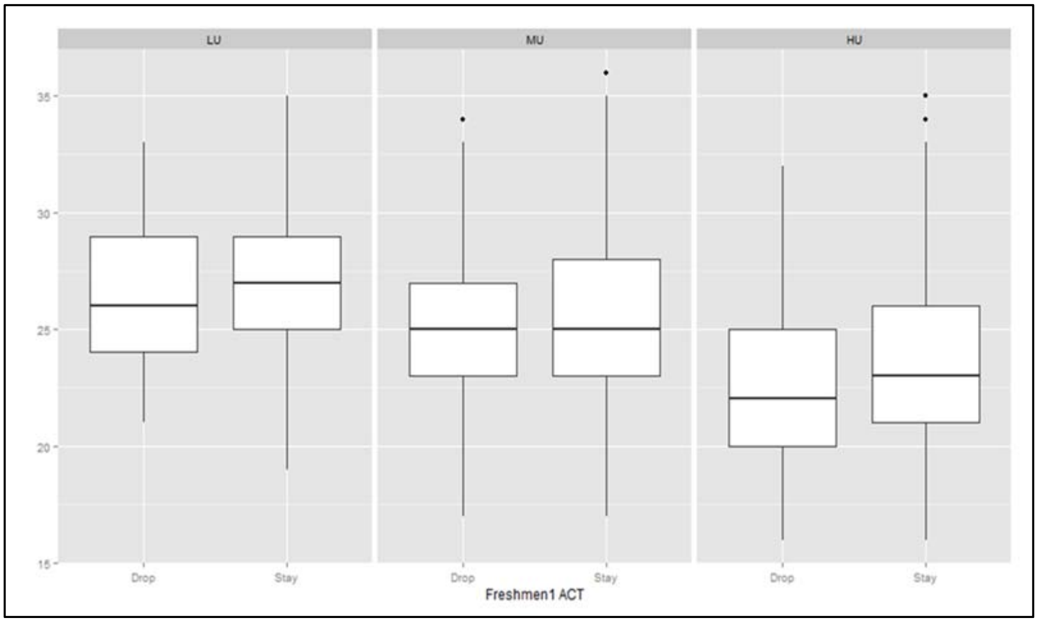

Figure 3: Boxplot comparing ACT of Drop vs. Stay for each URS Class. Sample sizes are as follows: LU Stay = 324, LU Drop = 42, MU Stay = 2012, MU Drop = 369, HU Stay = 707, HU Drop = 203

Table 2: Breakdown of statistics illustrated in Figure 3

Interval	Drop or Stay	Mean ACT	Min	Max
LU	Drop	26.73	21	33
LU	Stay	27.2	19	35
MU	Drop	25.1	17	34
MU	Stay	25.62	17	36
HU	Drop	22.74	16	32
HU	Stay	23.49	16	35

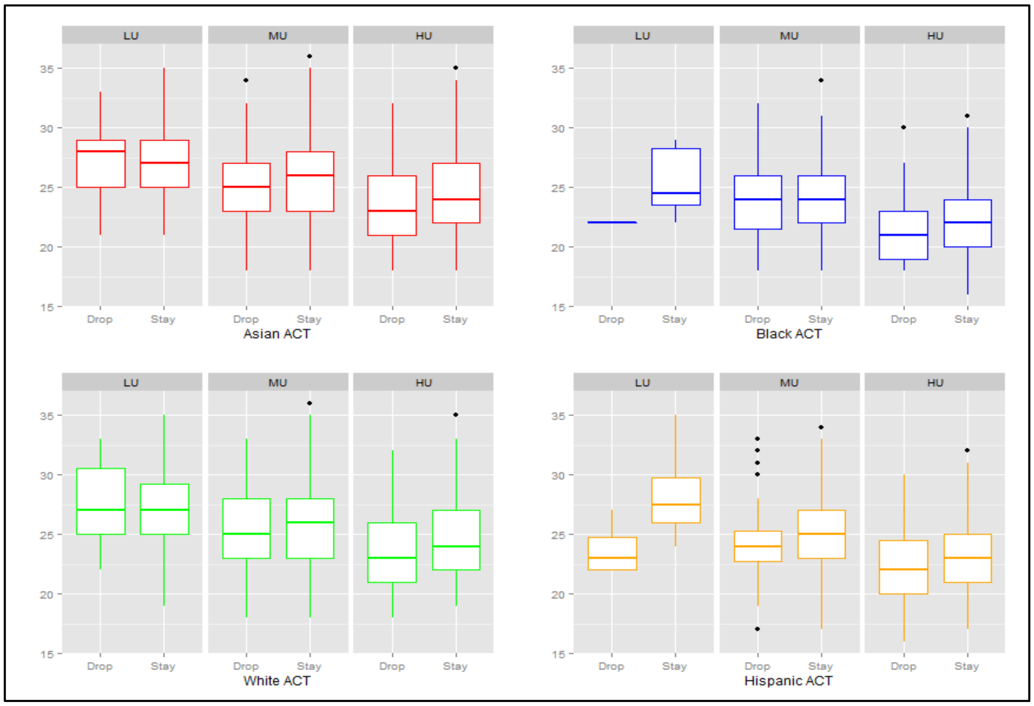

Figure 4: Boxplot comparing ACT of Drop vs. Stay for each URS Class by Race

Table 3 shows the p-values that resulted from using the t-test when comparing the mean ACT of students that dropped out and students that did not drop out within a class. The mean ACT scores of students that dropped out are statistically the same as students that did not drop out. Table 3 also shows the correlation coefficient for each class that shows the dependence between ACT and drop event within each class.

Table 3: P-values when comparing average ACT students of students that dropped out and students that did not. Testing with an α level of 5%.

	LU	MU	HU
P value of T-Test	0.843	0.348	0.229
Correlation	0.0430	0.013	0.060

Based on the results reported in Table 3, it is concluded that the ACT scores within each class for students that drop out and students do not drop out are random. The average ACT of the students who drop out and those that do not drop are statistically the same.

Second Criterion

Our second criterion is that the proportion of students who drop out within each class should increase as the class URS increases. A proportions test was carried out to compare the dropout rate between the classes. Testing with an α level of 5%. We first compared the proportion of drop out between LU and MU. This is shown in Equation 3.

$$H_0: P_{LU} = P_{MU} \tag{3}$$

$$H_1: P_{MU} > P_{LU}$$
$$P_i = proportion\ of\ student\ that\ dropped\ out\ in\ the\ i^{th} interval$$

Using the proportions test we obtain a p-value of 0.044 and fail to reject our null hypothesis. When comparing MU and HU (see Equation 4), we obtain a p-value of approximately 0.

$$H_0: P_{MU} = P_{HU} \tag{4}$$

$$H_1: P_{HU} > P_{MU}$$
$$P_i = proportion\ of\ student\ that\ dropped\ out\ in\ the\ i^{th} interval$$

Therefore, we can conclude that the second criterion is satisfied. A visual representation of this is also shown in Figure 5.

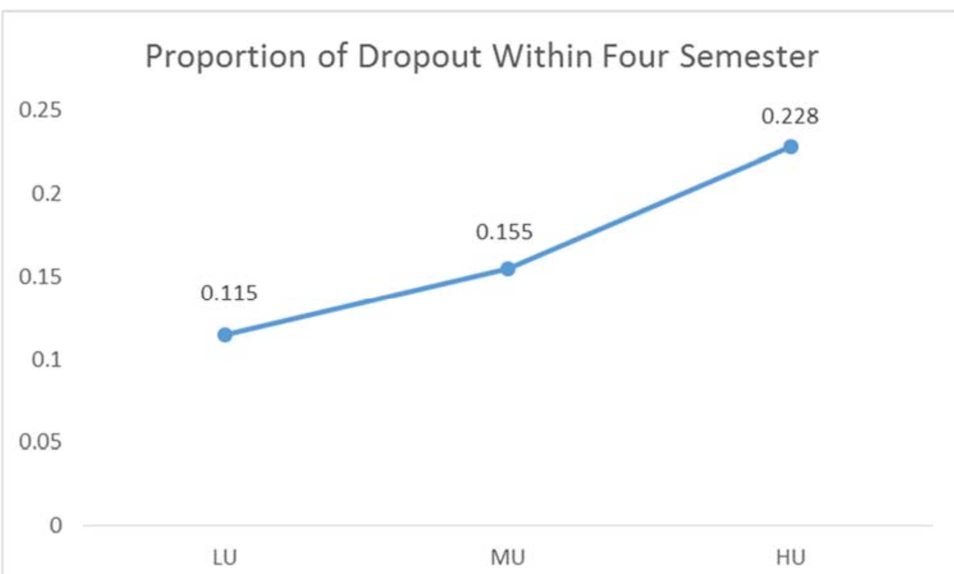

Figure 5: Proportion of Dropouts for each URS Class

V. Discussion

After constructing the URS classes, we now use them to track educational performance indexes of the students in each class.

Average Number of Times Students will take for Standard Math Course

All the students in our data set have to take a sequence of MATH1, MATH2, MATH3, and MATH4 courses. Each Math course is a prerequisite to its next in the sequence. A student has to take each Math course again if he/she fails to receive a grade of C or better. One index that can show the educational performance of student classes is the average value of the number of times that the students in each URS class take a given math course. We compared this number for MATH1 (taken when students enter the University as freshman—in their first semester) and MATH4 (taken in their fourth semester or later by each student) for each of the three URS classes (see Figure 6). Table 4 shows that there is a significant difference in average number of times a student takes MATH1 between each URS class. This indicates as URS increase, the average number of times a student takes MATH1 increases. This is due to the fact that students that come from underrepresented schools initially struggle. Normally, during the fourth semester, students take MATH4. As shown in Figure 6, the average number of times a student take MATH4 for each class is almost the same. This is further shown in Table 4, as the p-values are greater than 0.05. Table 5 shows the variance, upper and lower bound of each classes for each course. The upper and lower bound for each class in Table 5 confirm our observations made earlier where the expected number of times a student takes Math 1 increases as URS increases, whereas the expected number of times a student takes Math 4 is the same between URS classes. The converging of average values for MATH4 among the three URS classes shows that the educational performance of students in MATH4 are similar regardless of their URS class. A common misreading of the MATH4 average values comparison is that by the fourth semester all the academically poor students have already dropped out and the students who stay till the fourth semester are perhaps smarter students. However, as shown by the *First Criterion*, there is no relationship between the dropout event and the average ACT score of students in each class. Therefore, for the students in each class, the dropout event cannot be a representative of their scientific capacity of academic performance potential. Our conjecture is therefore that the students who made it to the fourth semester are successful because they have adequate learning conditions, and are motivated.

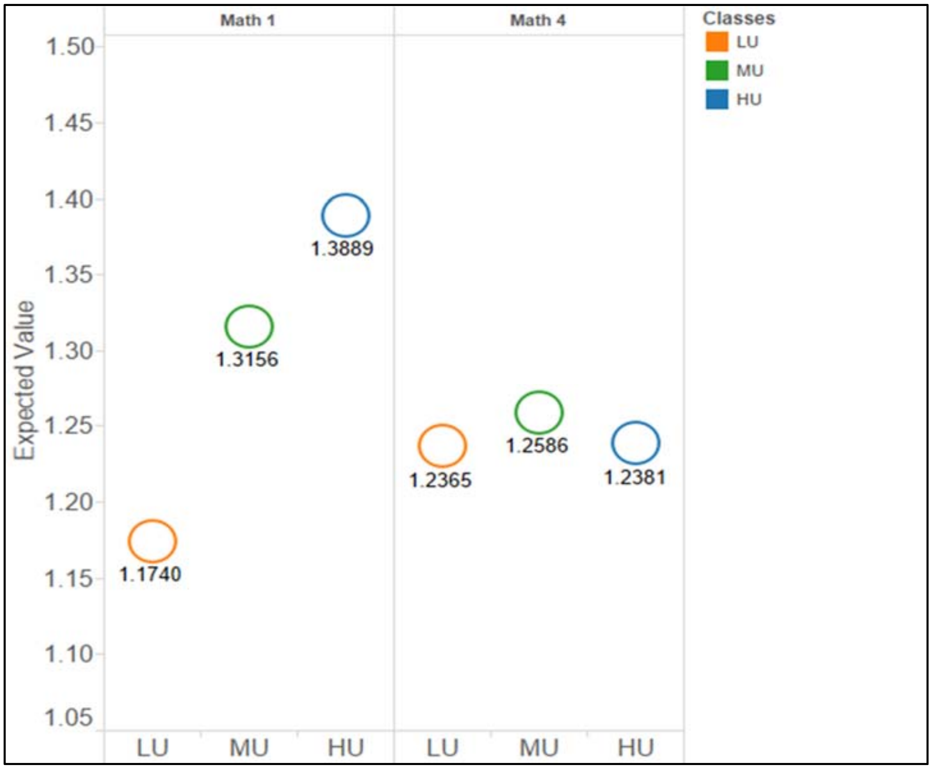

Figure 6: Comparison of the Average Number of Times MATH1 and MATH4 are taken by each URS Class.

Table 4: Shows the P-Values for each Hypothesis test comparing Average Number of Times a Course is Taken. Testing with an α level of 5%.

Course	Null Hypothesis	Alt. Hypothesis	P-Value	Conclusion
MATH1	$\mu_{LU} = \mu_{MU}$	$\mu_{LU} \neq \mu_{MU}$	<0.0001	Reject H_0
	$\mu_{MU} = \mu_{HU}$	$\mu_{MU} \neq \mu_{HU}$	0.0007	Reject H_0
	$\mu_{LU} = \mu_{HU}$	$\mu_{LU} \neq \mu_{HU}$	<0.0001	Reject H_0
MATH4	$\mu_{LU} = \mu_{MU}$	$\mu_{LU} \neq \mu_{MU}$	0.3646	Fail to Reject H_0
	$\mu_{MU} = \mu_{HU}$	$\mu_{MU} \neq \mu_{HU}$	0.6522	Fail to Reject H_0
	$\mu_{LU} = \mu_{HU}$	$\mu_{LU} \neq \mu_{HU}$	0.4920	Fail to Reject H_0

Table 5: Shows the Expected Values, Variance, Lower Bound, and Upper Bound for each interval for each course.

Course	Expected Value	Variance	Upper Bound	Lower Bound
MATH1	1.17	0.30	1.23	1.12
	1.32	0.26	1.33	1.30
	1.39	0.19	1.42	1.36
MATH4	1.24	0.39	1.32	1.15
	1.26	0.36	1.29	1.23
	1.24	0.54	1.31	1.16

Race as a Non-Factor

When addressing the admission of underrepresented populations, race is a common topic. Our URS classes are not dependent on a student's race. However, there is a correlation between our classes and race. Figure 7 shows the number of students from each race who are in the individual URS classes. When examining races that are minorities, African American and Hispanic, it can be seen more students are from higher URS classes. Where the majority of African American and Hispanic students originate from the HU class, there are a significant number of White and Asian students in MU. This shows that, where race and class may be correlated, not every student in a race can be treated the same. Therefore, the background (family, income, etc.) of these students becomes the key factor.

It is important to note that the high school's information does not necessarily match that of the student attending it. This requires administration to look deeper into an individual before giving them any admission advantages. This would be for both students from disadvantaged backgrounds that attend advantaged high schools and for students from advantaged backgrounds that attend disadvantaged high schools.

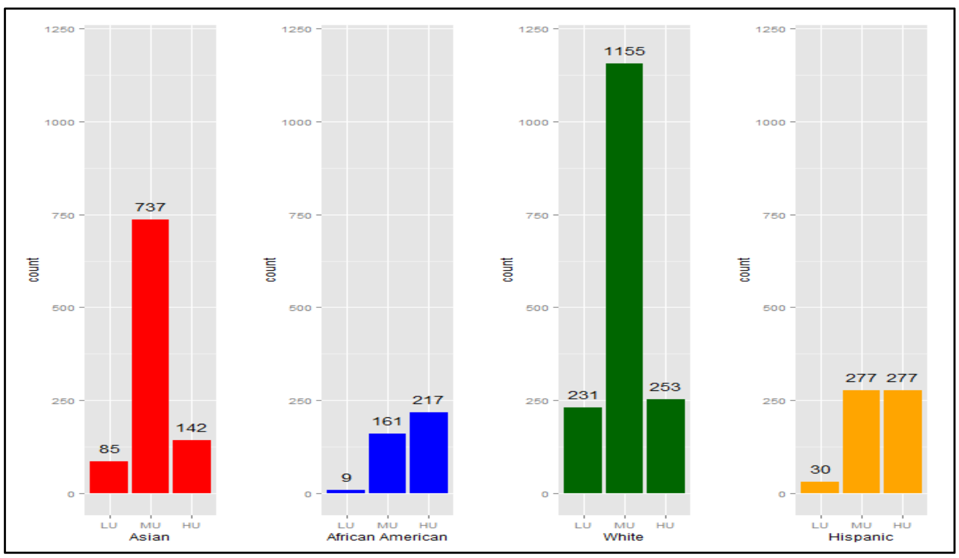

Figure 7: Number of Students within a Class by Race

Determining New Admission Rules

The URS classes created in this study can be used to derive a new support system of admissions at our University. Table 6 shows an example that illustrates how the URS classes can be used to simulate the enrollment of underrepresented applicants. This example does not reflect our university's standards or the ACT scores of our applicants and it is merely a hypothetical scenario.

Here we are assuming that our hypothetical university is currently using a minimum ACT of 27 to admit all its applicants regardless of their URS classes. We would like to know how this admission policy can be modified based on the generated URS classes' information. Table 6 shows the modification process. First, for each URS class we calculated the average ACT score from the data. We then normalized the average ACT scores by dividing the average ACT score for each class by the maximum average ACT score of all the classes (in this case 30.5). The normalized ACT scores (or weights) were then used to modify the minimum ACT requirement for each class. For the LU class we kept the minimum ACT of 27 and revised the minimum ACT for MU and HU classes by multiplying their normalized ACT weight by 27. Based on the revised policy, the applicants who belong to higher underrepresented classes (MU and HU) and do not satisfy the minimum ACT of 27, will not be automatically denied admission. Again, we emphasize that the final admission decision for each applicant must be based on a careful examination of the applicant's file. The admission rules derived in Table 6 will only prevent automatic admission denial actions based on the minimum ACT score for some underrepresented applicants, and these rules should not be used for final admission decisions.

Table 6: Hypothetical Values for New ACT Standards

	Average ACT	Normalized ACT (Weight)	Minimum ACT Requirement
LU	30.5	1.000	27
MU	28.1	0.921	25
HU	26.4	0.866	24

VI. Concluding Comments

It was shown that by using the URS we can create a framework for admitting underrepresented students. The new framework is currently examined by the Office of Admissions at our university's College of Engineering. The URS can be used to improve the admission chances of underrepresented students, and as a consequence increase the number of minorities admitted. Our study shows underrepresented students have a higher dropout rate in their first three semesters compared to the rest of the students. However, after completing the first four semesters, these students perform equally well as the rest of the students. The average number of times a student will take a higher level math course is about the same for underrepresented students and students that are not underrepresented.

These new rules must come with an increased effort to retain these students. Our introduction analyzed some retention methods being used at other universities and community colleges. We would recommend that some new form of retention be put in place but will not make suggestions on how to do so in this paper. Our URS classes can be used to detect which students might need more support in order to be retained.

VII. Future Work

This study was limited to students that came from high schools that had a CRI and TED and high schools that send more than one student per year to our university. Further studies can done in developing a URS for students that come from schools without this limitation. A model can be developed to impute URS. This support system can be expanded to other majors and department. High schools may not have a URS due to the lack of CRI or TED. For those schools, URS can be imputed by comparing student attributes for students at UIC that come from those schools. Another area of research can be related to the selection of different retention policies based on URS information.

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