Broadening Participation in Engineering through a Research Center-based Mentoring Program (Research)

Dr. Eduardo Santillan-Jimenez, University of Kentucky

Dr. Eduardo Santillan-Jimenez is the director of a mentoring program based at the University of Kentucky Center for Applied Energy Research (UK CAER) – and funded by the Broadening Participation in Engineering program of the National Science Foundation – designed to increase the number of African Americans, Hispanics and Native Americans graduating with engineering degrees and pursuing academic careers. Originally from Mexico, Dr. Santillan-Jimenez joined UK first as an undergraduate research intern and then as a graduate student performing his doctoral research at UK CAER and at the University of Alicante (Spain). After obtaining his Ph.D. in 2008, he worked as a postdoctoral fellow at Utrecht University (The Netherlands) prior to retuning to UK CAER, where he now holds the position of Principal Research Scientist. His current research focuses on the application of heterogeneous catalysis to the production of renewable fuels and chemicals, with emphasis on the upgrading of waste and algae oils to drop-in hydrocarbon fuels. His synergistic activities include leading and participating in a number of K-20 educational initiatives designed to increase and broaden participation in STEM fields.

Miss Sarah Hodges, University of Kentucky

Sarah Hodges, is a senior in the Chemistry Department at the University of Kentucky. She is originally from Knoxville, Tennessee, is a University Patterson Scholar and a student in the Lewis Honors College. Since 2016 Sarah has conducted research at the University of Kentucky Center for Applied Energy Research (CAER). Initially, she worked under the mentorship of Dr. Bob Jewell and Dr. Tristana Duvallet in the Environmental and Coal Technologies group at UK CAER, where her work focused on the piezoelectric effects of Ettringite in CSA cement and the effect on the formation of Ettringite in CSA cement of different solutions. Sarah joined the Biofuels and Environmental Catalysis Group in 2017 under Dr. Mark Crocker and Dr. Eduardo Santillan-Jiminez, where her work was one of UK CAER's first collaborative projects with the University of Grenoble Alps Pagora Engineering School of Pulp and Paper processing. Focusing on the thermochemical degradation process of cellulosic biomass during conversion to bio-oil, Sarah traveled to Grenoble, France for three months to begin her research and has since continued the project at UKCAER. In her time at UK CAER Sarah has been awarded a UK Summer Research Grant, a Kentucky Established Program to Stimulate Competitive Research, Research Scholars Program (EPSCoR RSP) Grant, and a National Science Foundation International Research Experience for Undergraduates (NSF iREU. In addition, she was awarded a Midwest Coal Ash Association Research Stipend and was the youngest person to ever win an American Coal Ash Association Educational Foundation Scholarship in 2017. Sarah is also a member of UK's student chapters of NSBE (National Society of Black Engineers), SWE (Society of Women Engineers), SHPE (Society of Hispanic Professional Engineers), SPORES (Student Participating in Outreach through Research in Engineering and the Sciences) and the Energy Club and has regularly volunteered with NERD SQUAD (a Lexington STEM Education non-profit foundation) since 2015.

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1. Background

1.1. The entrenched nature of minority underrepresentation in higher education and engineering

In spite of affirmative action efforts spanning several decades, African Americans and Hispanics are more underrepresented at American top colleges and flagship universities than they were in 1980 (Ashkenas, Park, & Pearce, 2017). The issue of underrepresentation is also observed in engineering, as illustrated by the fact that African Americans and Hispanics respectively received 4.1 and 11.1% of the engineering bachelor's degrees awarded in the U.S. in 2017 (Yoder, 2017), a year in which these groups comprised 13.4 and 18.1% of the U.S. population (U.S. Census Bureau, 2017). Therefore, the urgency to find ways to broaden the participation of underrepresented minorities (URMs) in engineering is shared by institutions across the nation. This includes a representative public flagship, land-grant, R1 university in the Southeastern U.S., which is in great need of innovative strategies to tackle the challenge of improving diversity in a College of Engineering that is rapidly growing in enrollment (see Tables 1 and 2, where the term "minority" encompasses African Americans, Hispanics and Native Americans).

Table 1. College of Engineering minority enrollment in a representative public flagship, land-grant, R1 University in the Southeastern U.S.

Term	African American	Hispanic	Native American	Total BS enrollment	Minority % of the total
Fall 2008	49	18	10	1,818	4.24%
Fall 2009	61	21	6	2,087	4.22%
Fall 2010	74	36	5	2,344	4.95%
Fall 2011	71	42	5	2,481	4.76%
Fall 2012	79	60	7	2,733	5.34%
Fall 2013	90	75	4	2,909	5.81%
Fall 2014	108	94	4	3,085	6.68%
Fall 2015	105	126	2	3,269	7.13%
Fall 2016	127	123	3	3,393	7.46%
Fall 2017	129	148	2	3,382	8.25%

Table 2. College of Engineering minority graduates of a representative public flagship, land-grant, R1 University in the Southeastern U.S.

Academic Year	African American	Hispanic	Native American	Total BS graduates	Minority % of the total
2008-2009	5	1	0	324	1.85%
2009-2010	2	3	0	327	1.53%
2010-2011	6	4	1	327	3.36%
2011-2012	6	2	1	340	2.65%
2012-2013	11	8	1	395	5.06%
2013-2014	12	10	2	427	5.62%
2014-2015	9	12	0	480	4.38%
2015-2016	10	7	1	549	3.28%
2016-2017	12	15	0	631	4.28%
2017-2018	19	19	0	624	6.09%

1.2. The rationale for broadening participation in engineering through a research center-based mentoring program

Indeed, although there was a considerable increase in overall enrollment from 2008 to 2012, both the minority enrollment and graduation rates were well under the 2012 demographic for the percentage of African Americans, Hispanics and Native Americans in the state where this university is located (11.3%), not to mention the corresponding national demographic (29.9%) (U.S. Census Bureau, 2012). In short, albeit these data evinced a pressing need to broaden participation, they also showed an abundance of opportunity to do so at this institution. Against this background, and informed by the body of knowledge that surrounds these issues, a novel strategy was conceived to effectively broaden participation in engineering. This unique strategy harnesses the resources of university research centers staffed with non-faculty researchers into a type of mentoring initiative that had never been investigated in academia, at least to the authors' knowledge. This research center-based mentoring initiative – which was proposed to (and funded by) the National Science Foundation (NSF) Broadening Participation in Engineering (BPE) program in 2014 and launched in 2015 – has three main goals: 1) to improve URM enrollment and graduation rates in engineering; 2) to enhance the professional development of URM engineering students so they can become engineering professionals, academics, leaders and role models; and 3) to investigate if mentoring in research centers could be used to complement mentoring in traditional engineering departments.

A previous contribution (Santillan-Jimenez & Henderson, 2017) has summarized the body of knowledge surrounding the aforementioned issues, with special emphasis on the use of mentoring to improve higher education outcomes for students in general and for URMs in particular. In addition, this contribution described the challenges for mentoring in academic engineering departments, among which faculty role strain takes precedence (Bowen & Sosa, 1989; Boyer, 1990; Fairweather, 1996; Geisler & Rubenstein, 1989). Saliently, this very concern renders research centers into favorable environments for mentoring (Bozeman & Boardman, 2003), as their non-faculty research staff – who typically have lower teaching and administrative workloads than faculty – can be leveraged to increase the amount and frequency of student-mentor non-classroom contact, which has been reported to enhance student retention (Pascarella, Terenzini, & Feldman, 1991). The latter, along with the fact that literature is lacking in terms of the potential benefits of housing mentoring programs in research centers relative to traditional engineering departments, was used as a rationale for investigating the prospect of broadening participation in engineering through a research center-based mentoring program.

1.3. Description of the research center-based mentoring program implemented and assessed

Briefly, 10 or more incoming URM engineering students are recruited into this program each fall, the actual number lacking any arbitrary cap and instead being chosen to make up for any attrition shown by previous student cohorts. Other than interest in both the mentoring program and the research portfolio of the research center, the only recruitment requirement is for students to join the program as incoming freshmen (mainly to equalize exposure and curb the impact of the latter as a confounding variable). Indeed, while efforts are made to recruit balanced cohorts in terms of gender and ethnicity, neither high school nor standardized test performance are used as recruitment criteria. During recruitment and immediately upon arriving on campus, students meet with a College of Engineering counselor and a point of contact at a center for applied research (CAR). Students consent to participate in the program and their needs are assessed. Parenthetically, a survey employed to assess the needs and expectations of participating students afforded some recurrent answers, including receiving 1) support accessing opportunities to attain research and hands-on experience in the field; 2) assistance improving both study and time management skills; and 3) help deciding on a major and a career path as well as establishing a professional network. At the start of their first spring semester students tour the CAR and learn about its research groups and projects. Students, based on their interests and preferences, are then matched with a CAR mentor. Students are involved in research projects and have access to ancillary services, facilities and support staff. Besides gaining laboratory experience, students working at the CAR receive credit towards a degree and/or compensation. In addition, students gain authorship in journal articles, attend scientific conferences to present their results, and participate in a number of outreach efforts. Throughout their college years, students are helped acquire and develop the skills they need to succeed – including academic and study skills, research skills, communication skills, teaching skills, funding procurement and project management skills, and outreach skills – by their counselor, their CAR point of contact and their mentor, who also leverage a variety of university resources. This arrangement avoids understaffing, a design flaw commonly found in mentoring programs (Haring, 1999). Indeed, reliance on just one individual incurs programmatic risks that can be alleviated by involving more individuals in a larger effort, since several facilitators can enlist and provide access to resources, focus the group on its goals and provide logistical support.

1.4. Previously reported results

In a previous contribution (Santillan-Jimenez & Henderson, 2017), initial results gathered through the assessment of the research center-based mentoring program described above were presented. Albeit these initial results suggested that a research-center based mentoring program can indeed improve both academic performance and retention, the data available corresponded to a fairly small sample and a relatively short period of time. This precluded the type of data analysis necessary to identify *statistically significant* effects of the intervention on retention and/or performance. Data acquisition has continued in the intervening years, resulting in a larger sample spanning a longer period of time. The results of the analysis performed on the assessment data acquired to date represents the main focus of this contribution.

2. Assessment

2.1. Assessment of previous mentoring studies

In terms of assessment, previous mentoring studies have displayed a number of limitations. These include longitudinal limitations caused by the fact that data collection has taken place at a single point in time and by the fact that most studies have displayed a pre- and post-design (Jacobi, 1991), as well as cross-sectional limitations mostly caused by the lack of control groups (Crisp & Cruz, 2009; Gershenfeld, 2014; Paglis, Green, & Bauer, 2006). In view of all this, a quasi-experimental design including both cross-sectional and longitudinal components has been deemed necessary (Cook & Campbell, 1979). Therefore, the assessment of the research center-based mentoring program described above was designed with these considerations in mind.

2.2. Assessment of the present mentoring study

First, both the initial 4-year duration of the program and the fact that data is being collected at multiple and regular intervals ensures the availability of longitudinal data that may in turn help determine the amount of time it takes for mentoring effects to emerge and the length of time that these effects persist (Jacobi, 1991). Moreover, data is being acquired for both a treatment group – URM engineering students participating in the research center-based mentoring program to broaden participation in engineering (BPE) – and for a control group (URM engineering students not participating in this program). This provides the type of cross-sectional data necessary to determine the effect of the intervention on both retention and performance. Saliently, this experimental approach offers important advantages over a true randomized experiment, as it avoids both denying mentors to students who want them and imposing mentors on uninterested students, which has been identified as an ethical concern (Gershenfeld, 2014).

In the following section, the raw data acquired to date is shown, followed by the description of a) the data analysis performed to identify *statistically significant* effects of the intervention on retention and performance; and b) the results of said analysis.

3. Results

3.1. Retention and performance data collected to date

Figures 1 and 2 show the raw data collected to date in terms of retention for the treatment and control groups per cohort per semester (Figure1) as well as performance (GPA) for both groups per cohort per semester (Figure 2). Values shown can be deemed “end-of-semester” data, since data acquisition for a given semester takes place after final values become available once the semester ends.

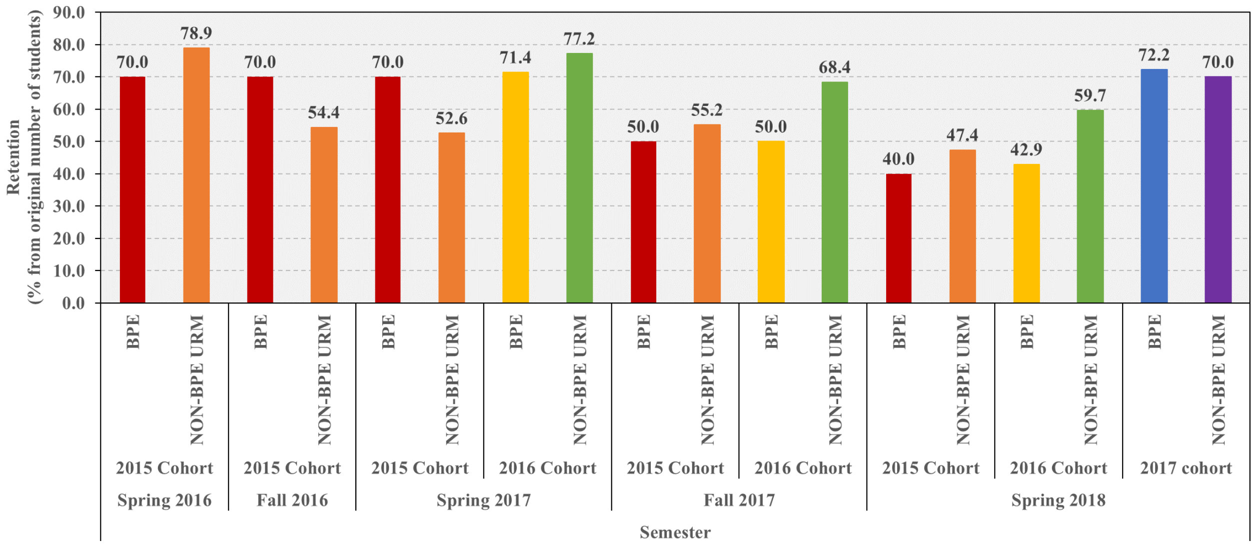

Figure 1. Retention for treatment (BPE) and control (non-BPE) URM students in the College of Engineering of a representative public flagship, land-grant, R1 University in the Southeastern U.S.

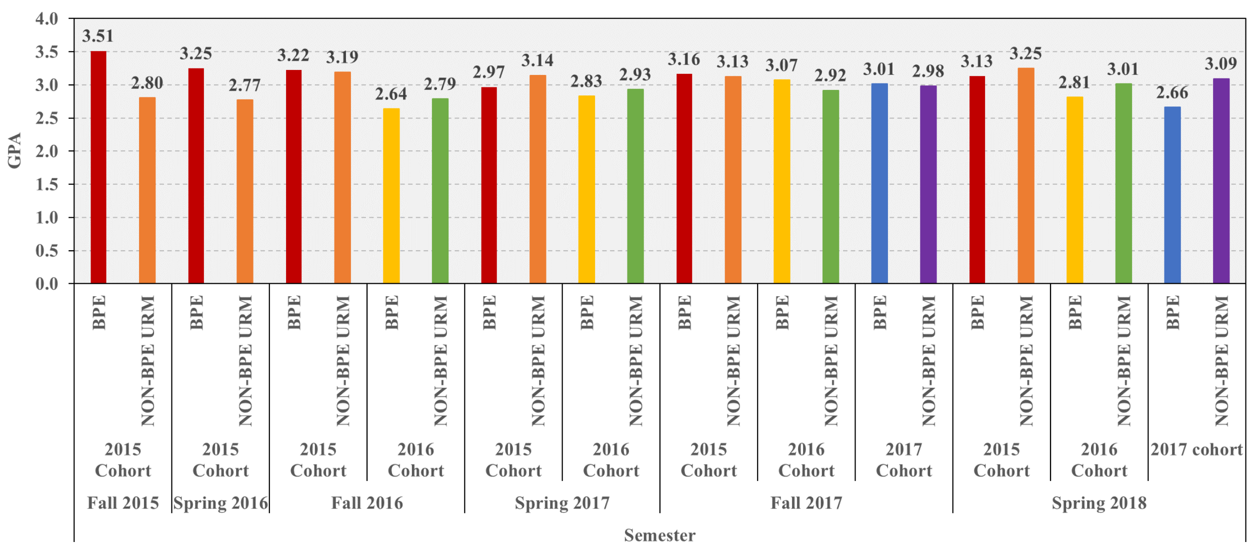

Figure 2. Performance for treatment (BPE) and control (non-BPE) URM students in the College of Engineering of a representative public flagship, land-grant, R1 University in the Southeastern U.S.

3.2. Statistical analysis of retention and performance data collected to date

In an effort to identify *statistically significant* effects on retention and performance attributable to the treatment – i.e., student participation in the mentoring program described in Section 1.3 – the raw retention and performance data above was analyzed using only the information of students involved in the program for at least three semesters. The reason for not using data from students involved in the program for only one or two semesters is that, in stablishing associations, student averages were used in order to reduce variability. The variability of data corresponding to students for whom only one or two semesters worth of data is available is much higher, which could bias the conclusions. Means and standard errors were calculated for each semester to illustrate the evolution of grades over time, results being shown in Figures 3 and 4.

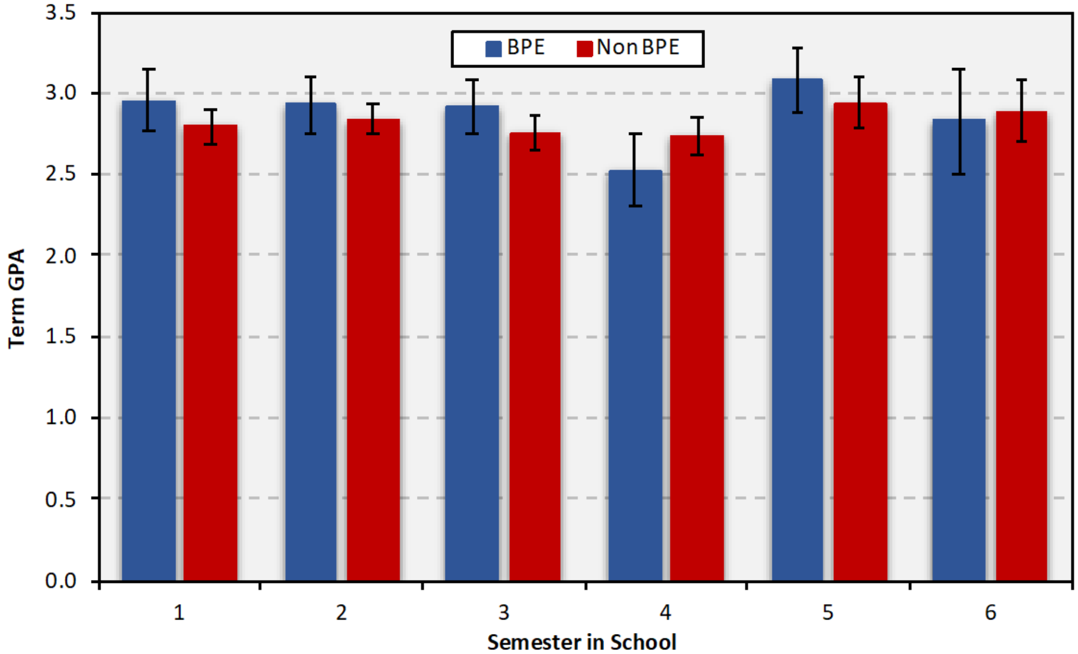

Figure 3. Term GPA by semester for treatment (BPE) and control (non-BPE) URM students in the College of Engineering of a representative public flagship, land-grant, R1 University in the Southeastern U.S.

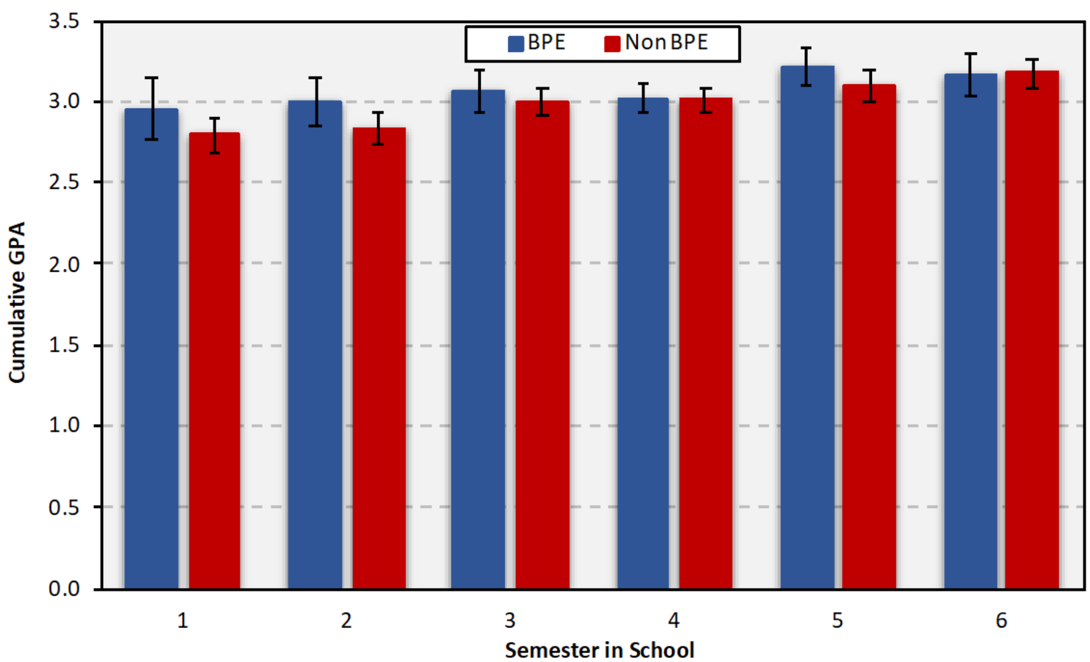

Figure 4. Cumulative GPA by semester for treatment (BPE) and control (non-BPE) URM students in the College of Engineering of a representative public flagship, land-grant, R1 University in the Southeastern U.S.

In order to find *statistically significant* differences between the treatment and control groups, both term and cumulative GPA averages were calculated and used as outcomes for modeling. The use of averages further reduced variability in the model and avoided model complications with repeated measures as described by Bland and Altman (Bland & Altman, 1995).

Linear models were built following a backwards selection method to incorporate variables that could influence the differences observed and reduce any potential sample bias (e.g., comparisons were made between students with similar ACT scores, same gender, ethnicity, etc.). In addition to the aforementioned linear regressions involving GPAs, logistic regression models were built for retention both within the College of Engineering as well as within the institution. Initial predictors used were ACT score, high school GPA, ethnicity, gender, residency status (in-state vs. out-of-state) and intervention group (treatment vs. control). Parenthetically, the aforementioned predictors were chosen considering both the accessibility of data representing different variables and their anticipated influence on outcomes. Intervention group was kept in the model to elucidate its importance for each outcome. Final models for the different outcomes are shown in Tables 3-6. Per standard notation, asterisks denote statistical significance (ascribed to p-values <0.05). In Tables 3 and 4, partial eta squared values are shown to illustrate the effect size in the regression models. In Tables 5 and 6, odds ratio and confidence interval (CI) values are used (instead of estimates) to illustrate the effect size in the logistic regression models.

Table 3. Parameter estimates for term GPA (R^2=0.43)

Term	Estimate	Std Error	t Ratio	Prob>|t|	Partial Eta Squared
Intercept	-2.220722	0.54065	-4.11	<.0001*	
Residency Status	-0.138183	0.065694	-2.10	0.0373*	0.03220
Intervention Group	0.1113658	0.086578	1.29	0.2006	0.01229
Highest ACT or Equivalent SAT	0.0504544	0.020414	2.47	0.0147*	0.04391
High School GPA Unweighted	1.0620582	0.147331	7.21	<.0001*	0.28095

Table 4. Parameter estimates for cumulative GPA (R^2=0.49)

Term	Estimate	Std Error	t Ratio	Prob>|t|	Partial Eta Squared
Intercept	-2.307921	0.510185	-4.52	<.0001*	
Residency Status	-0.141878	0.061992	-2.29	0.0237*	0.03789
Intervention Group	0.1477466	0.081700	1.81	0.0728	0.02400
Highest ACT or Equivalent SAT	0.0414498	0.019263	2.15	0.0332*	0.03364
High School GPA Unweighted	1.2027705	0.139029	8.65	<.0001*	0.36010

Table 5. Parameter estimates for retention in Engineering† (pseudo-R^2=0.1)

Term	Odds Ratio	95% CI LB	95% CI UB	ChiSquare	Prob>ChiSq
High School GPA Unweighted	5.117597	2.270926	11.53265	15.51	<.0001*
Intervention Group	1.6372058	0.6266541	4.2773878	1.01	0.3143

†For log odds of yes/no; LB=Lower Bound; UB=Upper Bound

Table 6. Parameter estimates for retention in institution† (pseudo-R^2=0.19)

Term	Odds Ratio	95% CI LB	95% CI UB	ChiSquare	Prob>ChiSq
High School GPA Unweighted	10.29578	4.107548	25.80689	24.73	<.0001*
Intervention Group‡	0.6753461	0.2219079	2.0553227	0.48	0.4894

†For log odds of yes/no; ‡Non-BPE/BPE; LB=Lower Bound; UB=Upper Bound

4. Discussion

Figures 3 and 4 above illustrate the evolution of grades as a function of time (semesters) in college, bars corresponding to semester means and error bars corresponding to the standard errors associated with the means. Tellingly, intervals from error bars overlap in almost all semesters. This can be interpreted as the absence of statistically significant differences; however, in all cases – except term GPA for the treatment (BPE) group – students on average finished higher than they started. Notably, the intervention group does not seem to show any different pattern when looking at values without adjusting for other variables that could bias the results. Tables 3-6 show final models for four different outcomes. The most interesting model in terms of the effect of the intervention – or treatment (BPE) group difference – is that shown in Table 4. Indeed, for cumulative GPA, a trend towards significance (p-value <0.1) was found for the difference between treatment and control groups when adjusting for residency status, ACT score and high school GPA. This trend showed that treatment (BPE) students averaged higher on cumulative GPA than students in the control group (non-BPE students). These results add to the knowledge base regarding the effect that mentoring has on the performance of URM students in engineering, which has been observed and reported in the literature to various degrees. Indeed, whereas some authors have reported GPA data showing positive – yet ultimately inconclusive – trends in this regard (Marszalek, Snauffer, Good, Hein, & Monte, 2005), some other authors found an intervention including a mentoring component to have a positive impact on outcomes (including GPA) through a methodologically rigorous study (Graham, Caso, Rierson, & Lee, 2002). While the other outcome models (represented by Tables 3, 5 and 6) do not show significant differences between the groups, all outcomes are shown to be significantly associated with high school GPA. Moreover, ACT scores are significantly correlated with both GPA outcomes, but not with retention values. Finally, the fact that residency status (in-state vs. out-of-state) is significantly associated with both GPA outcomes represents another interesting finding. Indeed, out-of-state students score significantly higher on average than in-state students.
Finally, it is important to recognize the limitations of the present study, which are mainly associated with the fact that the treatment group has been relatively small, tracked for a short period of time and restricted to a single location. Indeed, additional, more statistically significant, and/or more generalizable trends are expected to arise from the study of larger treatments groups for longer periods of time at multiple and distinct locations. For the purposes of the present study, a more complete data set will enable the repeated measures analysis necessary to study differences in individual semesters, which may in turn help determine the amount of time it takes for mentoring effects to emerge and the length of time that these effects persist. Insights gained in this manner can help answer questions such as whether mentees with lower grades or scores at the outset show greater improvements and/or whether the intervention is particularly effective for students at certain times in their matriculation. However, such repeated measures analysis would

be underpowered with the data set currently available, which is why the approach proposed by Bland and Altman (Bland & Altman, 1995) was employed.

5. Conclusions and outlook

In short, the statistical analysis of the data acquired to date shows a trend towards significance for the difference between treatment and control groups when adjusting for high school GPA, ACT score and residency, the treatment group showing superior performance – in terms of cumulative GPA – than the control group. Both performance and retention were found to be associated with high school GPA, while ACT scores and residency were found to be correlated with performance, out-of-state students outperforming their in-state counterparts.

The fact that data collection is ongoing is quite propitious, since that will allow for the statistical analysis of a more complete set of data, which will include information for additional semesters as well as for more students. The latter is expected to modify the results of the statistical analysis described above, potentially elucidating either additional and/or more statistically significant differences.

Notably, the results acquired to date in this study point to several research directions that could be pursued. Indeed, the analysis of additional information from similar treatment groups at other universities may help elucidate how generalizable the results are across different institutions in terms of ownership (public vs. private), size (large vs. small), type (high vs. moderate research activity) and/or location. Specifically, the analysis of analogous data acquired in situations where tuition does not differ for in-state and out-of-state students – e.g., in private universities or for students participating in either regional or specific tuition discount programs (Pitsker, 2016; Powell, 2018) – could be used to further probe the correlation between performance and residency. Admittedly, since some of these programs have GPA, SAT and/or ACT requirements, these variables would need to be controlled; however, this issue could be addressed by leveraging the fact that some institutions do not require exceptional academic credentials to waive out-of-state tuition for residents or certain states (Powell, 2018). Moreover, the inclusion of additional predicting variables (e.g., first-generation college student status, financial need) could help reduce any possible sample bias. Last but certainly not least, analyzing a larger data set comprising more students would help reduce variability and provide a better picture vis-à-vis the role that predicting variables play in determining outcomes in general and retention in particular.

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