Learning in Clusters: Exploring the Association Between Noncognitive and Affective Profiles of Engineering Students and Academic Performance

Dr. John Chen, California Polytechnic State University, San Luis Obispo

John Chen is a professor of mechanical engineering at Cal Poly. His interests in engineering education include conceptual learning, conceptual change, student autonomy and motivation, lifelong learning skills and behaviors, and non-cognitive factors that lead to student success. Prior to joining the faculty at Cal Poly, he was a faculty member at Rowan University.

Jenna Michelle Landy, California Polytechnic State University, San Luis Obispo

Jenna Landy is a senior at Cal Poly, San Luis Obispo, graduating in June 2020 with a Bachelor’s degree in Statistics and a minor in Data Science. In her third year, she began working with this group carrying out statistical analysis of survey data and has enjoyed learning more about engineering education.

Mr. Matthew Scheidt, Purdue University at West Lafayette

Matthew Scheidt is a Ph.D. student in Engineering Education at Purdue University. He graduated from Purdue University with a B.S. in Mechanical Engineering, The Ohio State University with a M.S. in Mechanical Engineering with a focus in Ultrasonic Additive Manufacturing. Matt is currently part of Dr. Allison Godwin’s STRIDE (Shaping Transformative Research on Identity and Diversity in Engineering) research group at Purdue. Matt’s research interests include engineering student success, both quantitatively and qualitatively. He is also interested in military veterans success in engineering.

Mr. Justin Charles Major, Purdue University at West Lafayette

Justin C. Major is a fourth-year Ph.D Candidate and National Science Foundation Graduate Research Fellow in the Purdue University Engineering Education Program. As an undergraduate student at the University of Nevada, Reno (UNR), Justin completed Bachelor’s degrees in both Mechanical Engineering and Secondary Mathematics Education with an informal emphasis in engineering education. Through his involvement in the UNR PRiDE Research Lab and engagement with the UNR and Northern Nevada STEM Education communities, he studied student motivation, active learning, and diversity; developed K-12 engineering education curriculum; and advocated for socioeconomically just access to STEM education. As a Ph.D. Candidate with the STRiDE Research Lab at Purdue University, Justin’s dissertation research focuses on the study of Intersectionality Theory and the intersectionality of socioeconomic inequality in engineering education, use of critical quantitative methodology and narrative inquiry to understand the complex stories of engineering students from traditionally minoritized backgrounds, and the pursuit of a socioeconomically just engineering education.

Ms. Julianna Ge, Purdue University-Main Campus, West Lafayette (College of Engineering)

Julianna Ge is a Ph.D. student in the School of Engineering Education at Purdue University. At Purdue, she created and currently teaches a novel course for undergraduate engineering students to explore the intersections of wellbeing, leadership, diversity and inclusion. As an NSF Graduate Research Fellow, her research interests intersect the fields of engineering education, positive psychology, and human development to understand diversity, inclusion, and success for undergraduate engineering students. Prior to Purdue, she received dual bachelor’s degrees in Industrial Engineering and Human Development and Family Studies from the University of Illinois at Urbana-Champaign. Her prior work experiences include product management, consulting, tutoring, marketing, and information technology.

Camaryn Elizabeth Chambers, California Polytechnic State University, San Luis Obispo

I am a 4th year mechanical engineering major at Cal Poly, and I’m interested in the aerospace industry. I am a part of Tau Beta Pi and the Society of Women Engineers on campus. My hometown is Hood River, OR where I love to ski, play tennis, and spend time with my friends, family and dogs.

©American Society for Engineering Education, 2020
Christina Grigorian
Michelle Kerfs, Cal Poly San Luis Obispo Statistics Department

Michelle is a third year statistics and data science student at Cal Poly San Luis Obispo. She recently joined this research team and is excited by what they can discover! She enjoys learning more about data analysis but in her free time also loves running, hiking, and any type of arts and crafts.

Dr. Edward J. Berger, Purdue University at West Lafayette

Edward Berger is an Associate Professor of Engineering Education and Mechanical Engineering at Purdue University, joining Purdue in August 2014. He has been teaching mechanics for over 20 years, and has worked extensively on the integration and assessment of specific technology interventions in mechanics classes. He was one of the co-leaders in 2013-2014 of the ASEE Virtual Community of Practice (VCP) for mechanics educators across the country. His current research focuses on student problem-solving processes and use of worked examples, change models and evidence-based teaching practices in engineering curricula, and the role of non-cognitive and affective factors in student academic outcomes and overall success.

Dr. Allison Godwin, Purdue University at West Lafayette

Allison Godwin, Ph.D. is an Assistant Professor of Engineering Education at Purdue University. Her research focuses what factors influence diverse students to choose engineering and stay in engineering through their careers and how different experiences within the practice and culture of engineering foster or hinder belongingness and identity development. Dr. Godwin graduated from Clemson University with a B.S. in Chemical Engineering and Ph.D. in Engineering and Science Education. Her research earned her a National Science Foundation CAREER Award focused on characterizing latent diversity, which includes diverse attitudes, mindsets, and approaches to learning, to understand engineering students’ identity development. She has won several awards for her research including the 2016 American Society of Engineering Education Educational Research and Methods Division Best Paper Award and the 2018 Benjamin J. Dasher Best Paper Award for the IEEE Frontiers in Education Conference. She has also been recognized for the synergy of research and teaching as an invited participant of the 2016 National Academy of Engineering Frontiers of Engineering Education Symposium and the Purdue University 2018 recipient of School of Engineering Education Award for Excellence in Undergraduate Teaching and the 2018 College of Engineering Exceptional Early Career Teaching Award.

Dr. Brian P. Self, California Polytechnic State University, San Luis Obispo

Brian Self obtained his B.S. and M.S. degrees in Engineering Mechanics from Virginia Tech, and his Ph.D. in Bioengineering from the University of Utah. He worked in the Air Force Research Laboratories before teaching at the U.S. Air Force Academy for seven years. Brian has taught in the Mechanical Engineering Department at Cal Poly, San Luis Obispo since 2006. During the 2011-2012 academic year he participated in a professor exchange, teaching at the Munich University of Applied Sciences. His engineering education interests include collaborating on the Dynamics Concept Inventory, developing model-eliciting activities in mechanical engineering courses, inquiry-based learning in mechanics, and design projects to help promote adapted physical activities. Other professional interests include aviation physiology and biomechanics.

Dr. James M Widmann, California Polytechnic State University, San Luis Obispo

Jim Widmann is a professor and chair of the Mechanical Engineering Department at California Polytechnic State University, San Luis Obispo. He received his Ph.D. in 1994 from Stanford University and has served as a Fulbright Scholar at Kathmandu University in Nepal. At Cal Poly, he teaches the College of Engineering’s interdisciplinary, industry sponsored, senior project class as well as course in mechanics and design. He also conducts research in the areas of creative design, machine design, fluid power control, and engineering education.
Learning in Clusters: Exploring the Association between Non-Cognitive and Affective Profiles of Engineering Students and Academic Performance

Abstract

This research paper explores the role of non-cognitive and affective (NCA) factors in influencing student achievement and thriving. We have developed and deployed a survey with evidence of validity and reliability to measure 28 NCA factors from $n=2339$ undergraduates at 17 U.S. institutions. The factors examined include personality, grit, meaning and purpose, engineering identity, mindset, motivation, test anxiety, test and study environment, perceptions of faculty caring, self-control, stress, gratitude, mindfulness, and sense of belonging. The results from a previous cluster analysis identified four distinct clusters of students’ NCA profiles, accounting for 69.0% of the sample. A second analysis indicated that membership within any of the four clusters was only weakly, if at all, associated with academic performance, as measured by self-reported, overall grade-point-average. In this study we explore this association in more detailed and nuanced ways to assess whether cluster membership is truly unassociated with academic performance.

Introduction

There is growing awareness that innate talent – i.e., IQ or intelligence – is neither the only nor the most important trait for predicting a wide range of achievement outcomes in adults or younger populations from adolescents to university students. Many non-cognitive traits (i.e., traits not directly related to the acquisition of knowledge) and behaviors have been shown conclusively to have a significant impact as well, including, for example, optimism [1], self-discipline [2], self-esteem [3] and grit [4]. Using a survey instrument developed through a multi-institution research collaboration [5, 6], we have identified a collection of non-cognitive factors that can account for over 26% of the variance in a student’s GPA, well above the 10% variance that the SAT/ACT score can predict [7].

While there is a myriad of ways to characterize students’ NCA profiles, a recently completed cluster analysis using Gaussian Mixture Modeling has identified four distinct clusters of students using these NCA factors, and the model accounted for 69.0% of participants [8]. An included preliminary analysis indicated that membership within any of the four clusters was only weakly, if at all, associated with academic performance as measured by self-reported, overall grade-point-average (GPA). We seek to explore this association in more detailed and nuanced ways to assess whether (a) cluster membership is truly unassociated with academic performance, or (b) one or more clusters is associated with differential academic performance. If the finding is the latter, the results would naturally suggest the need for interventions to support those students whose profiles may predict poor academic outcomes. Despite this paper’s focus on academic performance as the measure of success, we acknowledge that achievement or thriving by undergraduate engineering students cannot be simply measured by GPA when many other factors are at play. This study is necessary, however, since grades and retention are currently the predominant measures of progress and achievement in higher education.
Background on Completed Cluster Analysis

Our survey instrument was developed through a collaborative and deliberative process [5] between three partner institutions and underwent successive analyses to establish evidence of validity and reliability [6]. As of early 2019 it had been deployed nationally with $n=2339$ undergraduates at 17 U.S. institutions of varying institutional profiles. The 28 factors examined include the constructs of personality, grit, meaning and purpose, engineering identity, mindset, motivation, test anxiety, test and study environment, perceptions of faculty caring, self-control, stress, gratitude, mindfulness, and sense of belonging.

As a first analysis of the students’ NCA profiles, we chose cluster analysis using Gaussian Mixture Modeling (GMM), a person-oriented, probabilistic clustering technique [9] for a variety of reasons [8]. GMM builds and tests various models based on assumptions about three model parameters: the volume, shape and orientation of clusters. The analysis does not result in a single model but a vast number of them. Selection of the model with the best fit to the data is based on several fit metrics that rely on both objective and subjective judgments. Our modeling tested 9000 total models and we concluded that a four-cluster model was the best fit for these data [8]. In summary, the four clusters can be described as follows:

1. The **normative cluster**. Members of this cluster have factor means (average scores for each of the 28 factors) that were all similar to the overall sample mean, hence they form the normative group. This cluster is also the largest, accounting for 33.9% of the sample.

2. **High positive NCA factors but stressed**. Members of this cluster score higher for many traits associated with student success, including engineering identity, sense of belonging, gratitude and three of five dimensions of motivation. These students, however, are also characterized by high stress, which is unique to this cluster. This group accounts for 20.3% of the sample.

3. **Unconnected and closed off**. These students are low in several factors that have previously been correlated with lower academic performance, including engineering identity, and three of five facets of motivation. This cluster is also unique in that they possess a lower score for openness to new experiences and connectedness, meaning they do not have clear vision of how current tasks lead to future goals. They account for 11.6% of the sample.

4. **Unconnected to engineering, faculty and peers**. Members of this cluster have similar characteristics to the previous cluster, but even lower scores for many traits associated with academic performance. They score lower than all other clusters for engineering identity, three of five facets of motivation, belongingness, agreeableness, gratitude, and perceptions of faculty support. This group is the smallest cluster, accounting for 3.3% of the sample.

Comparing the clusters found no statistically significant differences in each cluster’s demographic make-up, including race or ethnicity, year of study, or first- or continuing-generation status, with the exception that women made up a lower percentage of Cluster 3 ($p < 0.05$). There were also no statistically significant differences across clusters for standardized test scores or GPA. This result should be viewed cautiously in light of the bias in our sample for a
preponderance of first-year students (72.7%) and compression in this scale since, for the overall sample, the mean GPA was around 3.3 (B+) at the time of the survey administration.

**Research Questions**

For this study, we chose to examine in detail a subset of the sample that was used to conduct the cluster analysis. Specifically, we elected to study only participants from one university (‘University A’; n=387) since we have access to detailed transcript data for this subset, including grades for all courses, the time that each course was taken, other relevant information such as admitted and current major, and a familiarity with the curricula of each major and the university’s retention and advising policies.

As previously described, cluster membership was only weakly, if at all, associated with academic performance as measured by the self-reported, overall GPA. This measure is a relatively weak measure of academic performance since it has less meaning if it is very early in a student’s studies (e.g., in the middle of the first year), and it could include other courses that are less predictive of later performance in engineering, such as general education electives. To examine any possible linkage between cluster membership and academic success, we pose the following research questions:

- **RQ1**: Does GPA differ across the clusters?
- **RQ2**: Do the trajectories of GPA change across the clusters?
- **RQ3**: Does retention vary across clusters?

Each of these research questions is composed of separate, more nuanced ways of examining GPA and retention, which we describe in detail along with the results below.

**Methods**

**Data Collection**

The SUCCESS survey [6] was distributed either electronically (via Qualtrics) or on paper (as Scantron forms) to students in engineering classes at University A in early 2018. The local researchers gained access to the classes through personal contact with the instructors. There was no grade impact for completing the survey, although a few instructors chose to give a nearly inconsequential extra-credit value for its completion. All participants were entered into a raffle for $10 gift cards. The overwhelming majority of responses (>95%) was by Scantron, given the much higher response rate using this method. For the paper form, students were allotted around 30-40 minutes to complete the survey during their class. Other details of the survey may be found in [6]. The survey included an attention check (“If you are reading this, fill in option two”) and only surveys that correctly responded to this check and had non-indiscriminate response patterns (e.g., checking all option two’s) were retained.
Participants

The demographic profile of this subset is similar to the original sample [6], as is the distribution of this subset to the four clusters. Table 1 summarizes the demographic profile of this subset sample.

Table I: Demographic profile of participants at University A

<table>
<thead>
<tr>
<th>Race/ethnicity</th>
<th>Number of participants</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>White</td>
<td>229</td>
<td>57.5%</td>
</tr>
<tr>
<td>Asian</td>
<td>67</td>
<td>16.8%</td>
</tr>
<tr>
<td>Hispanic or Latinx</td>
<td>42</td>
<td>10.6%</td>
</tr>
<tr>
<td>Black or African-American</td>
<td>3</td>
<td>0.8%</td>
</tr>
<tr>
<td>Native American</td>
<td>2</td>
<td>0.5%</td>
</tr>
<tr>
<td>Multi-racial</td>
<td>37</td>
<td>9.3%</td>
</tr>
<tr>
<td>Declined to answer</td>
<td>18</td>
<td>4.5%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Gender</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>133</td>
<td>33.4%</td>
</tr>
<tr>
<td>Male</td>
<td>265</td>
<td>66.6%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>First-generation status</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Neither parent attended college</td>
<td>32</td>
<td>8.0%</td>
</tr>
<tr>
<td>Some college or 2-year graduate</td>
<td>29</td>
<td>7.3%</td>
</tr>
<tr>
<td>4-year graduate or post-graduate education</td>
<td>327</td>
<td>82.2%</td>
</tr>
</tbody>
</table>

Data Analysis

Data were first reduced to focus only on students who were admitted to an engineering major upon entry to University A, dropping four individuals from physics, nutrition, or biochemistry majors. The current clustering included twenty individuals who fall into more than one cluster and 108 individuals who do not belong to any cluster. These individuals were also dropped from the analysis. Further, Cluster 4 was not included in the analyses because there were only 6 individuals in that group, making it unfit for statistical analysis. (We note, again, that this group exhibits traits that are perhaps the most worrisome among the clusters.) After removing these individuals, we are left with 147 students in Cluster 1, 69 in Cluster 2, and 37 in Cluster 3.

Overall GPA, engineering-specific GPA (only courses with an engineering prefix), and science- and math-specific GPA (only courses with a science and mathematics prefix) were calculated for each student and compared across clusters at this current time point, which represents approximately two years after the participants were first surveyed. These GPAs were also calculated for the end of each student’s first year. Each letter grade was converted to the standard 0-4 GPA scale (A = 4, A- = 3.7, B+ = 3.3, etc.), then an average was computed by
weighting course grades by their unit count. Courses taken credit/no credit and those where the student withdrew were excluded from calculation.

**Results**

*Research Question 1: Does GPA differ across the clusters?*

One-way ANOVA was carried out to test for differences in each GPA calculation between clusters using Type II sums-of-squares because of the unbalanced design. A Bonferroni adjustment of the significance level was used to account for six tests (overall significance level = 0.1, individual significance level of 0.1/6 = 0.017). Table II below shows the results of each test. Significant differences were only found across clusters for overall GPA (and nearly so for engineering GPA). To test for differences in overall GPA across clusters, Tukey’s honest significant difference (HSD) test for pairwise comparisons was used to determine which clusters were different from one another.

Table II: ANOVA results for difference in mean GPA across all clusters

<table>
<thead>
<tr>
<th>Model</th>
<th>GPA Measure</th>
<th>p-values</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Overall GPA</td>
<td>0.013 *</td>
</tr>
<tr>
<td>2</td>
<td>Overall GPA – Freshman Year</td>
<td>0.049</td>
</tr>
<tr>
<td>3</td>
<td>Engineering GPA</td>
<td>0.017</td>
</tr>
<tr>
<td>4</td>
<td>Engineering GPA – Freshman Year</td>
<td>0.099</td>
</tr>
<tr>
<td>5</td>
<td>Science and Math GPA</td>
<td>0.061</td>
</tr>
<tr>
<td>6</td>
<td>Science and Math GPA – Freshman Year</td>
<td>0.078</td>
</tr>
</tbody>
</table>

* = significant difference between clusters, p-value < 0.017

Pairwise testing found Cluster 3 to be significantly different from Cluster 2. With Tukey’s HSD, the overall average GPA of Cluster 2 is estimated to be between 0.06 and 0.60 grade points higher than Cluster 3. Figure 1(a) shows quantile box plots for overall GPA by cluster, while Fig. 1(b) shows average overall GPA with standard error bars by cluster.

![Quantile box plots for overall GPA by cluster](a)

![Average overall GPA by cluster](b)

Fig. 1: (a) Quantiles for Model 1, and (b) averages and errors for Model 1. Note that Cluster 4 has been excluded from the analysis because of small sample size.
Research Question 2: Do the trajectories of GPAs change across the clusters?

Here we focus on overall GPA and inspect whether the trajectory of a student’s GPA depends on their cluster membership. Figure 2 shows how the cumulative overall GPA progresses through a participant’s academic career, starting from their enrollment at University A as a first-time freshman student to the present. Figure 3 is a similar plot of GPA except that what is displayed at each time point is the GPA for that particular term (i.e. the weighted average grade of classes taken, for example, in spring term of their first year, as opposed to that of classes taken up until and including that term). Note that University A operates on a three-term academic year (fall, winter, spring). Very few participants enrolled in summer-term courses, so while these are included in the following terms’ cumulative GPA calculations, we do not inspect the summer term separately.
Fig. 2: (a) Trajectory of the average cumulative GPA of members of each cluster. (b) A detailed view of the trajectories on an expanded scale.
In viewing the average cumulative GPA (Fig 2), a strong and consistent pattern is that, for all clusters, a student’s first term is typically when they achieve their highest grades before they drop in the next term. Most clusters stabilize and stay relatively constant through the remainder of the first two years, with the exception of Cluster 3. Average quarterly GPA (Fig. 3) shows higher variation from term to term. Also consistent, and somewhat surprisingly, is the constancy of performance differences, even when they are slight, between the clusters. That is, regardless of the students’ point in their degree, Cluster 2 consistently outperforms Cluster 1, which consistently outperforms Cluster 3. While Cluster 1 and Cluster 2 GPAs remain relatively constant over time after the first term, a visual inspection suggests there may be a steady decline in Cluster 3’s cumulative GPA (Fig. 2(b)).

**Research Question 3: Does retention vary across clusters?**

To test this research question, we examined three models for retention. Major retention, R1, is whether a student has switched their major since admission. This represents the university’s official recognition of a change of major. Engineering retention, R2, is whether a student has switched from their engineering major since admission but is still attending University A in a non-engineering major. Finally, university retention, R3, is whether a student is a current student or not at the university as a whole. A chi-squared test for equal proportions was used to compare each retention rate across clusters. We compare p-values of these tests to the Bonferroni adjusted significance level accounting for three tests (overall significance level = 0.1, individual significance level of 0.1/3 = 0.033).
The proportion of students who have switched majors since admission (model R1) was not found to be significantly different between the clusters (p-value = 0.205). Since only two of 253 students included in the analysis officially switched to a major outside of engineering, the official rates of engineering retention, model R2, were not compared statistically. However, we estimated R2 by looking for individuals who did not take any engineering courses in the Fall term of their third year (which would be equivalent to retention after two years). Students at University A must go through a transition period before the switch is recorded by the Registrar’s Office, so this approach should capture students in that process. This test did not show any significant difference in engineering retention between the clusters (p-value = 0.419). Finally, the proportion of students who did not take any courses the fall term of their third year, model R3, was not found to be statistically different between the clusters (p-value = 0.35).

**Discussion**

In examining various GPA measures across clusters, differences were found for overall GPA only. The overall GPA of Cluster 2 was significantly higher than that of Clusters 3. The results reported here strengthen the original finding by confirming the differential performance between clusters but at a much later time (over one and one-half years, or five quarterly academic terms, after the original survey). None of the GPA measures based in the freshman year showed any significant differences, most likely due to stronger performance by students in general during the start of their freshman year (see Fig. 2), and this finding is consistent with our earlier finding based on self-reported overall GPA [8], with the exception that we could not include Cluster 4 in this analysis.

Although statistical tests could not be performed to measure differences in the trajectories of GPA between the clusters, an examination of these trajectories based on cumulative GPA (Fig. 2) and quarterly GPA (Fig. 3) was nonetheless enlightening. Differences between clusters, even when slight, were consistent over the two years for which data were available. The quarterly GPA further revealed that students across clusters generally performed well in their first academic term, and then immediately dropped in their second quarter of studies. The cumulative GPA trajectory of Cluster 3, the lowest academically performing cluster, shows perhaps a downward trajectory while the others seem to remain relatively constant. While the average GPAs of all clusters were acceptable to good (ranging from 2.9 to 3.4), for some students, if their GPA did not meet their expectation or goal, this could result in mental distress or lead to future performance decline. Finally, due to their small sample size, Cluster 4 has been excluded from all analyses. We noted earlier that Cluster 4’s NCA profile is similar to Cluster 3, but with even lower scores for many factors that correlate with academic performance. This cluster warrants more scrutiny with a larger sample.

Three models of retention were tested for differences across clusters and none were found to be statistically significant. This suggests that engineering students at University A left their majors at approximately the same rate from all four clusters examined. This result suggests that the NCA profile of students who leave engineering is not captured through the cluster analysis. In other words, students leave engineering for a variety of reasons beyond factors indicated through their NCA profiles, at least in so far as we have measured their NCA profiles. This is mildly surprising in light of our finding that some clusters possess worrisome scores for several factors that should be related to leaving, such as engineering identity, belongingness, motivation,
stress, and perceptions of faculty caring. One possible explanation may be the institutional characteristic of the engineering program at University A, which has one-year retention rate of >94%, and two-year retention rate of >85%. These rates are markedly higher than the national averages and may explain the lack of any correlation between the clusters and retention. It is possible that support programs and mechanisms to invoke those resources at University A are effective at retaining students who otherwise would not have persisted.

Summary and Conclusions

This study continues our research into how NCA factors can be used to explore and predict academic performance in engineering and computing undergraduates. At a single university, we have used true GPA measures and retention data across seven different terms to perform our analyses. We found no differential academic achievement across clusters during their first academic term, which confirms our previous results based on self-reported overall GPA for a much larger national sample. We found differential academic achievement across some of the clusters as they progressed through school. The trajectories of GPA across the clusters were found to drop sharply after the students’ first term in their studies and to stabilize thereafter, with the exception of the lowest-GPA cluster, which may be steadily declining. The numerical differences in GPA between the clusters, even when slight, were surprisingly consistent over the two years that we followed these students. Finally, we tested retention using three separate models and found no statistically significant difference between the clusters. Based on these findings, it is not clear whether cluster profiles can be used to predict retention or not.

Limitations and Future Work

The results presented here are limited by the relatively small sample size for some of the clusters. An immediate need is to duplicate this study with a much larger data set to confirm or refute the findings, and to clarify the academic performance characteristics of Cluster 4. The findings presented should not be extrapolated to other student populations since they are unique in the context of University A. Not only could student demographics and institutional characteristics (e.g., Ph.D. institution or M.S. only) be different, but institutional resources to support students may also be dissimilar and these could affect the outcomes of student performance.

The results presented here considered student academic performance during their first two years in engineering. We will continue to monitor their progress into years three and four where we typically see engineering GPAs fall, as well as perhaps significant changes to the students’ NCA profiles. Finally, we will be developing initiatives to address malleable traits in students that might hinder their academic success.

Acknowledgement

This material is based upon work supported by the National Science Foundation under Grant Nos. DUE-1626287, DUE-1626185, and DUE-1626148.) Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation. We would like to thank all the students who participated in this study. Without their time spent in thoughtful response, this work would not be possible.
References


