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Update on the Role of Non-Cognitive and Affective (NCA) Factors in Engineering and Computing Student Academic Performance

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Update on the Role of Non-Cognitive and Affective (NCA) Factors in Engineering and Computing Student Academic Performance

Abstract

The NSF-funded Studying Underlying Characteristics of Computing and Engineering Student Success (SUCCESS) project is exploring how non-cognitive and affective (NCA) factors relate to retention and broad definitions of success for undergraduate engineering and computing students. The main tool used in this study is the SUCCESS survey which provides insight into a student's Big5 personality traits (Neuroticism, Extraversion, Agreeableness, Conscientiousness, Openness), Grit (Consistency of Interest), Engineering Identity (Recognition, Interest), Mindset, Mindfulness, Meaning & Purpose, Belongingness, Gratitude, Future Time Perspectives of Motivation (Expectancy, Connectedness, Instrumentality, Value, Perceptions of Future), Test Anxiety, Time and Study Environment, Perceptions of Faculty Caring (Social Support, Empathic Faculty Understanding), Self-Control (Impulsivity), and Stress measures (Support, Reaction, Frustrations, Conflict, Changes). Over the last three years, the survey has been given to over 4,000 engineering and computing students nationally. It is postulated that understanding the interplay among NCA factors may impart a more in-depth understanding of engineering student success than traditionally tracked cognitive factors, such as standardized test scores and GPA. After identifying groups of NCA factors that are both malleable and important in engineering and computing student success, targeted NCA-based interventions are being developed that can become a critical tool for use by engineering departments, faculty and academic affairs professionals to enhance the student experience. This paper provides an update on progress to date on the overarching research goals with a focus on activities at one of the three collaborating institutions partnering in this work.

Background

The NSF-funded Studying Underlying Characteristics of Computing and Engineering Student Success (SUCCESS) survey was created and validated to ensure assessment of various non-cognitive (NCA) factors in engineering and computing science students. In an 18-month collaborative and iterative process involving researchers at three partner institutions: California Polytechnic State University, San Luis Obispo (Cal Poly), Purdue University and the University of Texas – El Paso (UTEP), constructs broadly related to student success were integrated into the survey. The SUCCESS survey has now assessed over 4,000 engineering students nationally over the course of four years and has provided valuable insight into the NCA profiles that exist within computing and engineering students. This paper focuses on data collected at Cal Poly, a primarily undergraduate West Coast University with a large engineering and computing College.

One purpose of the SUCCESS project is to utilize the information gathered through survey administration to explore student performance through new lenses that challenge traditional student assessment tools. Typically, student potential and preparedness for undertaking engineering and computing studies is determined via high school grade point averages and standardized test scores; however, these have been shown to be poor predictors of student performance trajectories in engineering and computer science education [1]. Instead, the SUCCESS survey measures the following NCA factors: Big5 personality traits (Neuroticism, Extraversion, Agreeableness, Conscientiousness, Openness), Grit (Consistency of Interest), Engineering Identity (Recognition, Interest), Mindset, Mindfulness, Meaning & Purpose, Belongingness, Gratitude, Future Time Perspectives of Motivation (Expectancy, Connectedness, Instrumentality, Value, Perceptions of Future), Test Anxiety, Time and Study Environment, Perceptions of Faculty Caring (Social Support, Empathic Faculty Understanding), Self-Control (Impulsivity), and Stress measures (Support, Reaction, Frustrations, Conflict, Changes). Independently, these factors have all been shown to demonstrate a relationship with student success measures. The SUCCESS project intends to identify student populations that may be at risk by using their NCA profiles to guide initiatives in support of students and have a positive impact on broadly defined measures of student performance.

The three overarching questions that guide this project are as follows:

- RQ1. What are the NCA profiles of engineering and computing students, and to what extent do profiles vary by institution, academic program, demographics, or over time?
- RQ2. In what ways are NCA factors predictors of academic performance, and how do they mediate a student's response to academic or personal obstacles they may face?
- RQ3. To what extent can NCA-based interventions improve academic performance and the perceived quality of the undergraduate experience, and how do students at different institutions experience those interventions?

In its final form, the survey measures 28 NCA factors that have been independently identified and reported by other researches including their relation to student success. Here we will provide brief descriptions of some of the constructs. See Scheidt [2] for a complete listing.

Self Control: This construct is formed by two sub-constructs: self-discipline and impulse-control. Self-discipline measures one's general ability to show restraint, and impulse-control measures one's impulsivity, or the degree to which a person's behavior is characterized by lack of forethought [3]. In previous studies, self-control has been linked to the ability to control alcohol and drug consumption [4], and it is also shown to be linked to academic success [5].

Big Five Personality Traits: The Big 5 personality test measures aspects of personality based on five different traits [6]. These are *Openness*, *Conscientiousness*, *Extraversion*, *Agreeableness*, and *Neuroticism*. The SUCCESS survey includes 15 items that measure Big 5 constructs, three dedicated to each factor of the Big 5 personality traits.

Grit: This construct was proposed by the psychologist Angela Duckworth and is defined as the passion and perseverance for long-term goals [7]. *Grit* is usually unrelated or inversely related to intelligence or talent. The two subcategories of grit are consistency of interest and perseverance of effort.

Test Anxiety: The Test Anxiety Scale is a construct included in the Motivated Strategies for Learning Questionnaire (MSLQ) [8]. It was created to measure students' worries, which can hinder performance (cognitive component) and physiological arousal aspects of their anxiety (emotionality component). It has been found that test anxiety is negatively related to academic performance and can lower success expectancies.

Time and Study Environment: Time management can range from setting aside a night for studying to weekly and monthly scheduling. Study environment refers to the setting where the student studies for class work.

Mindset: This construct is divided into two parts: growth and fixed mindset [9]. A fixed mindset construct is a mentality where an individual believes that there is a fixed ceiling for success and intelligence. On the other hand, an individual with a growth mindset believes that skills and intelligence are malleable and can be improve with effort and practice.

Survey Construction and Data Collection

Over a 18-month period in the 2016-2017 academic year, the PIs from the three collaborating institutions planned and developed the SUCCESS survey [10] which resulted in a pilot version deployed at two of the partner institutions. At Cal Poly the pilot survey was delivered using Qualtrics to 374 engineering and computing students. Exploratory Factor Analysis (EFA) was used to validate which questions to retain in the final version of the survey for the following year [11]. The final version of the Survey was printed on Scantron forms and delivered to 17 different Universities nationwide as well as to the three-partner institution. At Cal Poly, the survey was given to students largely in classroom settings which insured a high response rate. Table 1 shows the survey completions at Cal Poly for the last four academic years. In addition to survey collection for over 2500 survey results of Cal Poly students, we have successfully added student grades and student conduct data into the dataset which allows us to track academic performance as well as how students may respond to obstacles while in the academic setting. This data is de-identified and kept secure to protect the anonymity of the survey respondents.

Table I: Information on the surveys completed

Academic Year	Surveys Completed	Notes
2017-2018	321	Mostly Mechanical Engineering (M.E.) students
2018-2019	1253	All Engineering First Year students and Most M.E.'s surveyed
2019-2020	530	Only M.E. students surveyed
2020-2021	517 +Ongoing	All M.E. students via Qualtrics

Validation of Survey Results

In addition to the EFA of the pilot survey data, further validation of survey results were conducted using Confirmatory Factor Analysis (CFA) which showed the majority of the constructs provided valid results while a few did not and are no longer considered [12]. At Cal Poly, data from the 2017-2018 survey were benchmarked against the results from the nationwide deployment as well as against data reported by others in the literature for different student populations. Results indicated that the data from Cal Poly is largely identical to (and thus a fair sample of) the larger SUCCESS survey dataset, but in many instances, substantially different from reported results from the literature. The traits that differed substantially include *Self-Control*, *Extraversion*, *Neuroticism* and *Openness* from the Big 5 survey, and growth and fixed mindset beliefs from the mindset survey. Several reasons could explain these differences including variation due to different survey instruments being deployed, difference due to changes in culture over time and that students who choose to study engineering and computer science are actually different in many NCA traits from the non-engineering and non-computing undergraduate population. The SUCCESS survey may simply be exposing these differences. More details concerning the benchmarking efforts can be found in Widmann et al [13].

To further validate the survey, we performed a test-retest experiment by giving the survey to 115 Cal Poly students in order to determine the stability of the survey responses over time. The Test-Retest experiment occurred during the spring of 2020 when students were sheltering at home due to COVID-19 restrictions. Of the 28 NCA factors included in the survey, 25 passed the test-retest validly for all correlations across the four-week Test-Retest dates. The factors that passed the test include: The Big5 (Neuroticism, Extraversion, Agreeableness, Conscientiousness, Openness), Grit (Consistency of Interest), Engineering Identity (Recognition, Interest), Mindset, Mindfulness, Meaning & Purpose, Belongingness, Gratitude, Future Time Perspectives of Motivation (Expectancy, Connectedness, Instrumentality, Value, Perceptions of Future), Test Anxiety, Time and Study Environment, Perceptions of Faculty Caring (Social Support, Empathic Faculty Understanding), Self-Control (Impulsivity), Stress (Support, Reaction). The factors that failed the test-retest include: Stress (Frustrations, Conflict, Changes), indicating that they may not be stable over a short period of time. Since the data for this test was collected during a potentially stressful time for students, we hypothesize that the stability of these stress measures may have more to do with the COVID-19 pandemic than problems with the survey instrument. Note that many of the NCA factors are malleable over time with stress measures operating on shorter time scales which also supports this hypothesis.

Findings

With a very large and robust dataset, the collaborative research team has made significant progress in answering our fundamental research questions as well as exploring new questions as we perform the necessary data analysis. To explore RQ1 and RQ2, Scheidt [14] used national data from the initial deployment of the survey in 2017-2018 and found that engineering students NCA profiles fall into four discernable clusters. At the time, the data set included 2339 undergraduates at 17 different institutions. The clusters include:

- Cluster 1: The Typical Cluster (n = 832). Members of this cluster had factor means that were all similar to the overall sample mean.
- Cluster 2: High Positive NCA Factors but with a Fixed Mindset (n = 500). The members in Cluster 2 were generally high in many of the factors, with many statistically different from all other clusters.
- Cluster 3: Unconnected and Closed Off (n = 311). Members of this cluster displayed several factors that correlate to lower student success, including significantly lower means for engineering identity interest, belongingness, expectancy, instrumentality, and connectedness. Members of this cluster may include students who do not identify with engineering as a profession or as an academic field of study.
- Cluster 4: Without Feeling of Support from Faculty and Peers (n = 94). Cluster 4 has the fewest members and displays strongly negative values for several NCA factors that may predict lower student success. Members of this cluster scored lower than all other clusters

for engineering identity, instrumentality, perceptions of the future, expectancy, belongingness, agreeableness, and perceptions of faculty support.

Difference in Grade Point Averages Across Clusters

Tracking of Cal Poly students' academic performance over two years based on cluster membership indicated differences in academic progression [15]. Here, we are able to add a third year to our longitudinal dataset of Cal Poly student performance. To do this, a one-way ANOVA was carried out to test for differences in Grade Point Average (GPA) between clusters using Type II sums-of-squares because of the unbalanced design. A test was performed for Overall GPA, for Engineering GPA and for Science and Math courses GPA. A Bonferroni adjustment of the significance level was used to account for three tests (overall significance level= 0.1, individual significance level of 0.1/3=0.033). Table II shows the results of each test. Significant differences were found across clusters for overall GPA and engineering GPA.

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

GPA Measure	**P-value**
Overall GPA	0.009754*
Engineering GPA	0.02249*
Science and Math GPA	0.06328

* = significant between clusters, p-value < 0.033

Trajectory of GPA by Cluster

To further explore the academic performance of students in each cluster, we examined the trajectory of the average cumulative overall GPA, average quarterly overall GPA, an average cumulative GPA for College of Engineering Courses (CENG), and the average quarterly GPA for CENG courses over time. Figures 1-4 show how each clusters average GPA changes across the quarters since the students enrolled at Cal Poly. There are nine quarters for which the GPA calculated (Cal Poly is on a three-term academic year). These quarters are identified with the three terms (fall, winter, spring) and the number indicating the year at the university. Summer quarters were not included because they have very low enrollment numbers.

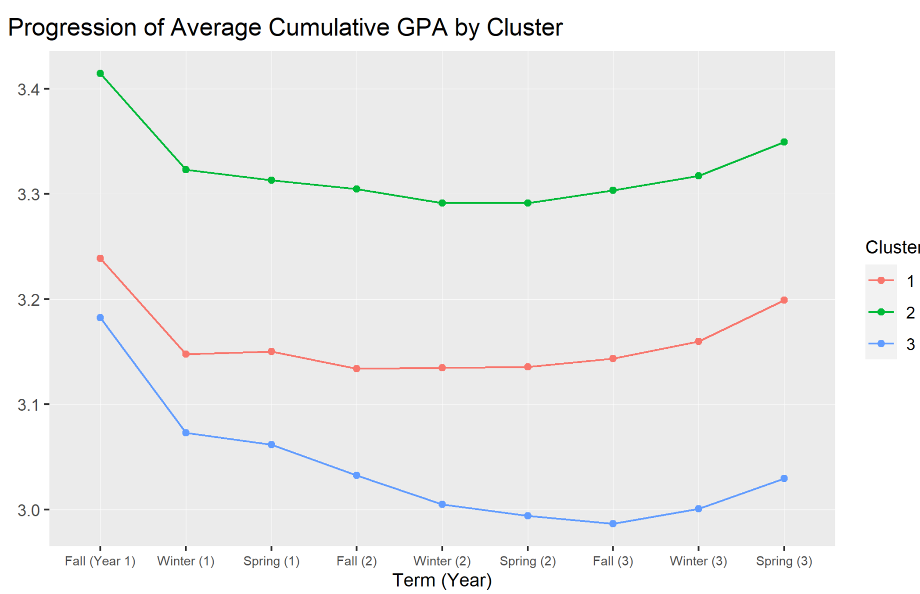

Fig. 1: Trajectory of the average cumulative GPA of members of each cluster on an expanded scale.

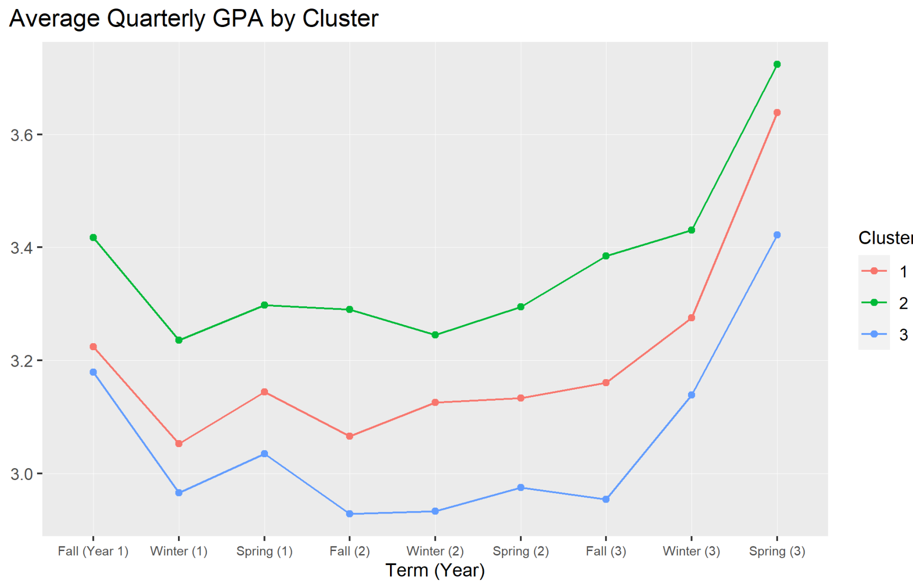

Fig. 2: Trajectory of the average quarterly GPA of members of each cluster on an expanded scale.

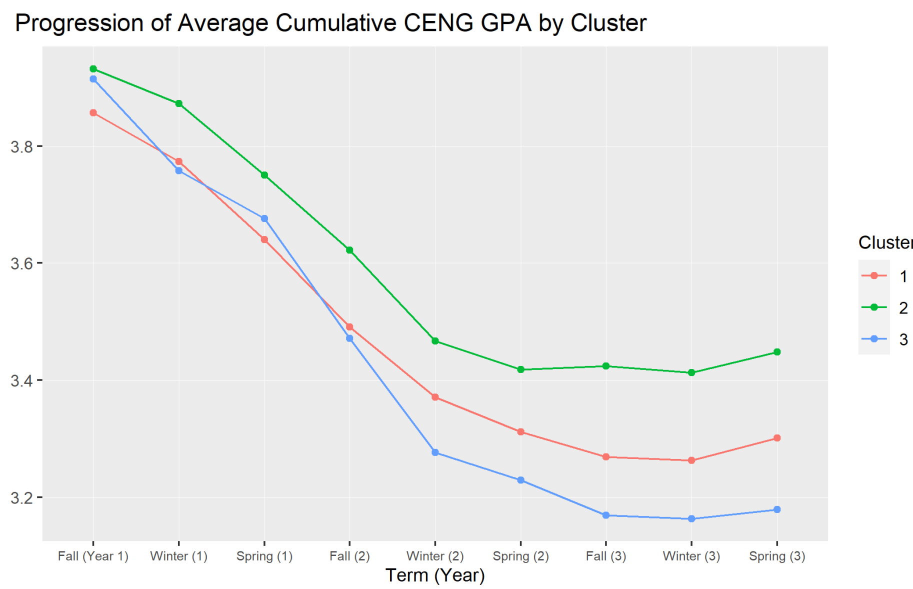

Fig. 3: Trajectory of the average cumulative engineering GPA of members of each cluster on an expanded scale.

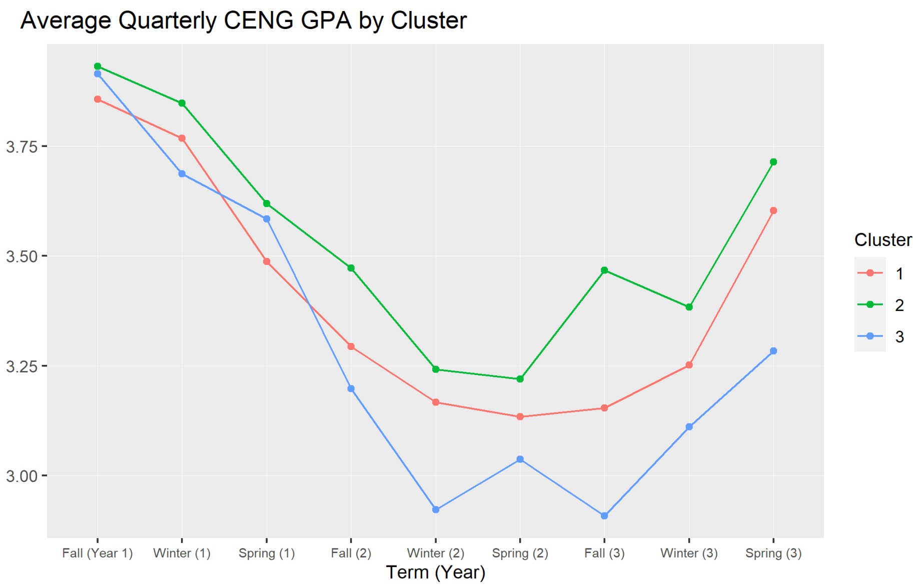

Fig. 4: Trajectory of the average quarterly engineering GPA of members of each cluster on an expanded scale.

Across all the graphs, the general pattern is that Cluster 2 has the highest average GPA, followed by Cluster 1 and then Cluster 3. Recall that Cluster 2 includes students with strong positive NCA factors but with a fixed mindset, and Cluster 3 includes students that display more factors associated with poor academic performance. There are only a few occurrences where the cluster trajectories cross. The first two figures focus only on overall GPA, and the grade point scales range from 3.0 to 3.4 for Figure 1, and 3.0 to 3.6 for Figure 2. Figures 3 and 4 focus solely on GPA made up from classes within the engineering college. These graphs have a grade point scale ranging from 3.0 to 4.0.

From Figure 1 we see that the clusters exhibit similar behavior for average cumulative GPA. The common pattern is to start with the highest GPA for the first quarter then experience the largest decline before generally flattening out and a slight incline towards the end of the third year. For our data specifically, Winter (3) and Spring (3) may display unusual behavior due to COVID-19 pandemic. Winter (3) concluded with virtual finals, and some classes canceling finals entirely. This may have caused slightly higher GPAs than usual. Spring (3) saw the biggest change, as many departments at Cal Poly offered for all or most classes to be taken as credit/no credit and allowed this decision to be made late in the quarter. This would heavily influence the average GPAs because students could choose to only count the classes they were doing well in towards their GPA. Because cumulative GPA is weighted by the number of units being graded, the pandemic did not affect cumulative GPA nearly as much as it did quarterly GPA.

Figure 2 shows the changes through each quarter, and the noticeable difference caused by the pandemic in the final quarter of our data. We see a dramatic increase for the final quarter, because students' quarterly GPAs were skewed because most classes were eligible for credit/no credit grading. The quarterly GPAs show more variation quarter to quarter than the cumulative GPAs. The different clusters still follow a similar pattern, with high GPAs for the first quarter before a sharp decline the next quarter. After that the other quarters don't change too drastically until Winter and Spring of the third year, but it is unclear if this is due solely to the pandemic or would have happened regardless.

In Figure 3, we see that all three clusters begin with their highest average cumulative engineering GPA in the first term, Fall (Year 1). After this term, there is a steady decline in GPA to Fall (Year 3) for Cluster 1 and Cluster 3. For Cluster 2, there is a steady decrease in GPA from Fall (Year 1) to Spring (Year 2) and then we see GPA level off. However, during Spring (Year 3), the average cumulative engineering GPA slightly increases across all three clusters which may be due to COVID-19. As mentioned previously, COVID-19 resulted in many departments offering classes to be taken as credit/no credit which could lead to students choosing certain grades to be counted towards their GPA. Regardless of the term, Cluster 2 consistently outperforms Cluster 1 and Cluster 3. Within the students' first three terms, the performance level between Cluster 1 and Cluster 3 interchange, but in the following terms, Cluster 1 consistently outperforms Cluster 3.

Figure 4 displays greater variation in average quarterly engineering GPA from term to term, emphasizing a sharp increase in GPA during the last term. This drastic increase may again be due to COVID-19 accommodations. Within Cluster 1 and Cluster 3, there is a lot of fluctuation in performance during years 2 and 3. Like the trends found within the average cumulative engineering GPAs (Fig. 3), the average quarterly engineering GPAs follow a similar pattern with the highest GPA occurring in Fall (Year 1) for all three clusters. Additionally, Cluster 2 constantly surpasses Cluster 1 and Cluster 3. The interchanging in performance level between Cluster 1 and Cluster 3 during the first year after enrollment is consistent with what we see in the average cumulative engineering GPA (Fig. 3). The range of average quarterly engineering GPAs is relatively the same as the range of GPAs in Figure 3.

Initiatives

Recently, we began exploring initiatives (interventions) that could be used to change malleable NCA factors in order to answer RQ3 of this project. During the spring of 2020, Cal Poly deployed the PERTS (Project for Education Research that Scales) [16] system to 243 students consisting of an intervention group (n=128), a control group (n=115). Mindset was measured pre-post intervention (which lasted 2 weeks) and then again 1 month later. Preliminary analysis of the results showed that the intervention created a small change in short-term growth mindset which persisted with a small effect. This study provided initial insight into how engineering and computing students might respond to non-cognitive interventions in terms of factors chosen, the format of the intervention and timing.

Discussion and Future Work

Over the next year will see many significant activities that will further explore our research questions with a special focus on RQ2 and RQ3. With the expansion of the dataset to include more longitudinal data on Cal Poly Mechanical Engineering students and the addition of Cal Poly student conduct data, we can continue to look at the relationships between NCA factors and how they influence a broad definition of engineering and computer science student success. We will be able to identify individual and groups of NCA factors that might be targets for initiatives to improve student success. Piloting of various initiatives will be used to determine their potential impact on larger populations. Specifically, we will:

- Examine the Cal Poly dataset closely and continue to identify NCA factors that predict student success for both traditional academic success (e.g. GPA, retention, graduation rates) and broader definitions of student success such as student thriving.
- Continue our longitudinal study of Mechanical Engineering students, by surveying all students in the major during the 2020-2021 academic year.
- Add academic performance data for year three and year four of Mechanical Engineering students in the study to complete the longitudinal dataset.
- Based on identified individual and groups of NCA factors that predict different forms of student success, we will develop and test interventions that develop these beneficial beliefs and attitudes in students.
- Continue to work closely with our collaborating institutions (Purdue and UTEP) to develop and pilot test initiatives as a means of changing NCA factors for students to improve student success.

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