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Institutional Characteristics and Engineering Student Non-Cognitive and Affective (NCA) Profiles*

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In our prior work, a cluster analysis (n = 2,339) identified four groups of engineering undergraduates' non-cognitive and affective (NCA) factors from a list of 28 dimensions such as belongingness, engineering identity, self-control, and perceptions of faculty caring. We found clusters of students that generally contained favorable student success characteristics (high belonging, high engineering identity, high motivation, and others), as well as those that were characterized by less favorable characteristics for student success (low belonging, low perception of faculty caring, and others). Higher education institutions have varying missions and profiles, and they serve different student populations. We hypothesize that as institutional characteristics are related to specific NCA (institutional characteristics may affect belongingness, stress support, perceptions of faculty caring, or other constructs from our NCA-based clusters), they may also be related to cluster membership. To test our hypothesis, we merged our dataset with institutional data from the Integrated Postsecondary Education Data System (IPEDS), engineering program enrollment data from the American Society for Engineering Education (ASEE) Engineering Data Management System (EDMS), and financial data from the U.S. Census Bureau. The final data for this analysis consisted of n = 1,252 responses across 14 U.S. institutions. We used multinomial logistic regression to predict cluster membership as a function of both individual and institutional characteristics. We found that institutional characteristics correlate to cluster membership in important ways: students at large and/or and doctoral granting institutions have decreased odds of being in a generally positive cluster containing favorable student success characteristics, while enrollment at guaranteed tuition institutions increases these odds. These results elevate the role of institutional culture and its alignment to student characteristics as a key component of successful student outcomes. These results, when considered as a question of student-institution alignment, offer opportunities to rethink student academic and social support structures that encourage growth in specific NCA factors. In turn, this growth may support expanded engineering student success.

Keywords: institution type; non-cognitive and affective factors; affective theories; academic support; student success

1. Introduction and Motivation

Between 2006 and 2015, the number of full-time students studying engineering increased by 63% [from 374,202 to 610,000 students; 1]. However, high attrition rates in engineering, especially for students from underrepresented backgrounds (i.e., women, socioeconomically disadvantaged, Black, Latinx, and Indigenous learners), remain a continuing concern among higher education stakeholders, including students and parents. Research shows that students in STEM, compared to non-STEM peers, are more likely to switch to non-STEM majors or not complete their degrees at all [2–4]. Further, studies also suggest that socioeconomic factors, perceptions of risk, and institutional climate play an important role in these decisions [5, 6]. In addition to the negative impact on students, high attrition strains U.S. organizations seeking a qualified, talented, and diverse STEM workforce. Therefore, STEM students' educational opportunity and success are essential to U.S. economic vitality, intellectual and creative leadership, and global competitiveness [7, 8].

Prior research on engineering student outcomes has examined students' tendency to switch majors or drop-out [9, 4, 10, 11]. These studies indicate that both cognitive skills (e.g., academic achievement) and non-cognitive attributes (e.g., perceptions of failure or success), as well as institutional characteristics, might contribute to students' retention and success in engineering programs. However, few studies have examined the role of student-institutional alignment on engineering student out-

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comes. In particular, much of the prior work on student NCA factors (identity, belongingness, and so forth) considers these factors to be *characteristics of the individual*, with only implicit connections to the institutional context in which these students study. There remains a substantial gap in our understanding of how institutional factors and individual attributes work in concert to shape student outcomes.

We begin to address this research gap by leveraging our prior work on student NCA profiles, augmented with institutional data and financial data, to explore the connections among these individual and institutional variables via multinomial logistic regression. We have previously reported on the existence of 4 distinct clusters of students based upon NCA profiles [12]. In this work we explore the hypothesis that alignment between individual and institutional characteristics plays a role in student NCA factors, clustering, and outcomes.

2. Background

Some institutions carry a reputation for their prestige in engineering, such as polytechnics and many land grant institutions. Those reputations can affect not only which students apply but, subsequently, who is admitted and who ultimately succeeds [13]. Therefore, studying engineering students from multiple institution types provides a unique glimpse into how institutional context relates to students and their non-cognitive profiles. In addition, measurements for many psychological factors that foster student success (e.g., personality and belonging) are domain-specific and therefore must be measured within the context they occur [14]. This study uses items that have validity evidence specifically with undergraduate engineering students, either through the previous work of others or through our own factor analyses. Focusing on engineering students across institutions allows us to (1) examine the effect of institution- and program-level characteristics while minimizing potential confounds (described later) and (2) uphold the validity of our measures. The first step in our study of institutional contexts and students' non-cognitive attributes thus begins with a literature review summarizing work on institutional differences and NCA factors linked to student success, and then drawing from these findings to tailor the current study to undergraduate engineering students across institutional contexts.

2.1 Historical Models to Understand the Student-Institutional Alignment

Substantial prior work acknowledges the key role played by institutional context in student success, and in particular the alignment or "fit" of a student within the institution occupies a central position within these models. This alignment manifests in several important processes, starting with the initial decision to enroll at a specific institution and continuing through future decisions about persisting through graduation. Hossler and Gallagher's [15] three phase linear model, which builds upon prior work [16, 17], progresses through predisposition, search, and choice processes. Each of these phases is affected by both individual factors (e.g., students), as well as organizational factors (e.g., schools and the universities) and the interactions among these variables. Hossler and Gallagher's [15] student attributes resemble certain NCA factors considered here, including both psychological and behavioral factors. Much of this prior work is rooted in classical models such as Astin's [18] I-E-O (inputs-environment-outcomes) model and Tinto's [19] Model of Institutional Departure. These historical models are useful in understanding student-institution relationships at a high level, but more recent scholarship highlights the tighter connections among academic preparation, academic and social-emotional support available at the institution, and student outcomes. For instance, the Model of Co-Curricular Support [20] adds valuable texture to the institutional support elements of the student experience by highlighting the role of peer interactions, faculty relationships, career counseling and advising, financial assistance, and many others.

Similarly, Mattern, Marini, and Shaw [21] provided additional depth to the student-oriented considerations about retention and transfer via a large-scale, cluster-based analysis that included academic preparation and financial resource measures. However, these and other more contemporary models lack specificity in both the measured constructs and the engineering student population. We next describe engineering-specific, modern constructs that individually correlate to student success.

2.2 NCA Factors, Student Outcomes, and Other Student Characteristics

Non-cognitive factors have largely been studied individually, and they have been described using the vocabulary of the specific disciplines [e.g., non-cognitive attributes, non-cognitive skills, non-cognitive factors, character skills, social-emotional learning, soft skills, personality traits; 22, 23]. Across disciplines and research studies, NCA attributes have been consistently shown to correlate with educational outcomes [24–26]. Non-cognitive attributes contribute to college grade point average (GPA) and retention – for instance, meta-analyses indicate that self-efficacy has the strongest correlation with college GPA and is the second-strongest predictor of retention [22, 27]. As one of many non-cognitive attributes, grit has also recently received attention in education research [although there is concern about what it means to be ''gritty'' and the privilege surrounding this measure; see 28–30], and is strongly and positively related to college GPA and college retention [31–33]. While the details of these studies vary (student population, outcome measure, study design), the general conclusion is that student success and NCA factors are connected, and that there exists a particularly desirable set of NCA factors for individual students to possess [34–37, and many others]. The malleability of certain NCA factors presents an opportunity for institutions to build academic or social activities to support students' growth of specific attributes.

We consider the role of socioeconomic inequalities in shaping non-cognitive attributes as well; we use socioeconomic status (SES) as a proxy. Sociologists have found that the parents of higher SES students have greater privilege to invest more time and economic resources in their children's educationally effective activities, which benefits students' cognitive and social-emotional needs [38, 39]. Lundberg [40] also found that Big Five conscientiousness predicted degree completion for all women, but only for high-SES men, while openness was positively related to degree completion for low-SES men. Given the well-documented importance of non-cognitive attributes for college outcomes, it is important to understand the intersectional role of SES in shaping non-cognitive attributes in varying institutional contexts to promote educational success for students, in particular marginalized students in engineering.

2.3 Research Question

Although a significant body of literature exists linking single or small numbers of NCA factors to student outcomes, little prior research explores the ways in which a large collection of NCA factors (such as via membership in a cluster) correlates to student outcomes, or the systematic connections of those NCA factors to institutional characteristics. Exploring the relationships between the NCA profiles of students and their individual demographics in conjunction with institutional characteristics will help us understand how institutional characteristics are related to NCA profiles – in ways that add value over prior research that considered a limited number of NCA factors in the absence of institutional context. Our prior work used a person-centered clustering approach to categorize engineering students into 4 clusters based upon their NCA factors, with some clusters exhibiting a set of characteristics linked to high student success, and other clusters showing sets of NCA factors connected to lower levels of success. In this study, we leverage this prior work to answer this research question: *in what ways do student NCA factors, their backgrounds and demographics, and institutional characteristics interact to predict cluster membership?* The underlying hypothesis is that alignment of individual-level and institution-level variables will predict cluster membership, which in turn allows us to infer conclusions about student outcomes.

3. Methods

3.1 Survey and NCA Factors

In prior work, we designed, tested, gathered validity evidence for, and then distributed, a large NCA factor survey to students at about 20 institutions across the United States. Amongst a large sample of solicited universities, institutions included in this work consisted of the 20 schools in our social network who chose to be involved after being solicited. The 28 NCA factors measured by the survey include: the Big Five personality traits, engineering identity, future time perspective (FTP) motivation, belongingness, gratitude, mindfulness, self-control, mindset, and several others. We chose these NCA factors because each has validity evidence as a construct in relation to student success. We conducted exploratory and confirmatory factor analysis, as well as cognitive interviews, to further obtain validity evidence for this comprehensive survey. More information about survey development, data collection, and validity evidence is contained in our prior published work [41–44].

3.2 Cluster Analysis

In other prior work, we used Gaussian Mixture Method modeling (GMM) to cluster the survey responses of $n = 2{,}339$ engineering students according to their measures across 28 NCA factors [12]. GMM is a person-centered, probabilistic clustering technique that assigns observations to clusters according to their probability of belonging to each cluster [45, 46]; observations not exceeding a given threshold are assigned to an unclustered group. Using a multiple-restart method, we generated 1,000 clustering models and reviewed a series of appropriate fit indices to determine the best clustering solution for our data. We found that a four-cluster model of students NCA profiles was the simplest, best fitting model. These clusters of students, based on their NCA makeup, were named to represent the overall NCA profile of the engineering students they contained. Full details on the process of clustering students, reviewing fit indices, and deciding upon the best solution can be seen in our prior paper [12].

The names and descriptions of the resulting clusters are shown below. Similarly, the numbers of participants total and at each of the 14 institutions included in the analysis we present are shown in Table 1.

- Cluster 1: "Normative" – Members of this cluster held NCA factor scores near the overall average of the sample of students in the cluster analysis. "Average" NCA factors are neither good nor bad, rather they represent a comparative baseline for other clusters (35.5% of sample).
- Cluster 2: "High Positive NCA Factors" – Overall, the average student in this cluster scored high on many NCA factors linked to student success, including stress support, support from faculty, future time perspective motivation (i.e., perceptions of the future, value, instrumentality, connectedness, and expectancy), gratitude, belongingness in engineering, meaning and purpose in life, engineering identity interest and recognition, time and study environment, and agreeableness, with correspondingly low scores on attributes like impulsivity and neuroticism (21.3% of sample).
- Cluster 3: "Unconnected and Closed Off" – In contrast to Cluster 2 which contained students with predominately higher NCA factor scores, this cluster contained students with low NCA scores on factors associated with student success including engineering identity interest, belongingness in engineering, and expectancy, instrumentality, and connectedness from the future time perspective motivation framework (13.2% of sample).
- Cluster 4: "Without Support from Faculty and Peers" – The fourth cluster was similar to the third cluster, with even lower scores on dimensions of engineering identity (interest and recognition), FTP motivation (instrumentality, perceptions of the future, and expectancy), agreeableness, perceptions of faculty support, and belongingness in engineering (4.0% of sample).

There were no statistically significant differences in self-reported standardized test scores or in GPA across clusters for this sample [12]. Additionally, the only significant (at $\alpha = 0.05$) difference in demographics (including institutions) across clusters was a lower percentage of women and non-binary participants in Cluster 3, as compared to the other clusters. In our previous analysis, about 26% of the sample remained unclustered using our GMM approach. Unclustered participants held NCA profiles diffusely distributed throughout the parameter space with no strong trends or commonalities (thus their lack of assignment to a cluster). The unclustered group demographics were similar to those of Clusters 1–4 in terms of race/ethnicity and year in school, and similar to Clusters 1, 2, and 4 in terms of gender.

Based upon the substantial prior literature about NCA factors, we expected that members of Clusters 1 and 2 are more likely to achieve success in engineering programs than members of Clusters 3 and 4, and our prior research focusing on GPA bears out this contention. We found that members of Cluster 2 (high positive NCA factors) had higher GPA on average than those in the other clusters. While GPA is not the only–or perhaps even the most important–element of student success, we nonetheless conclude that there is a hierarchy of clusters: we would prefer students to be members of Cluster 2 or perhaps Cluster 1, and we would like students to not be members of Clusters 3 and 4.

In more detailed analysis of participants' GPA over time at a single institution [47], we found that members of Cluster 2 maintained the highest GPA

Table 1. The percentage of cluster membership at each institution

School	Participants [Count]	Cluster 1 [%]	Cluster 2 [%]	Cluster 3 [%]	Cluster 4 [%]	Unclustered [%]
A	349	39	19	10	1	31
B	467	27	19	18	3	33
C	100	30	15	18	2	35
D	276	35	13	6	3	42
E	81	30	20	16	2	32
F	140	33	16	9	4	39
G	228	18	17	8	1	56
H	76	33	26	11	1	29
I	98	32	12	10	4	42
J	50	34	26	4	4	32
K	41	12	24	15	5	44
L	27	41	22	4	0	33
M	111	27	21	10	5	38
N	214	31	16	3	3	47

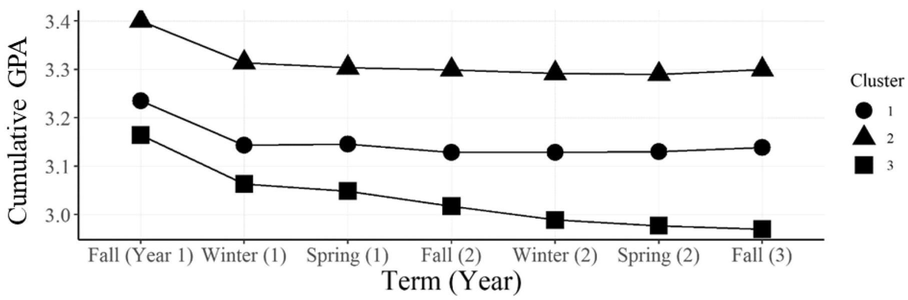

Fig. 1. GPA progression for a sub-sample of students at a single institution from Chen et al. [47]. Statistical differences exist between Cluster 2 and 3 at Fall of year 3. Cluster 4 was not included due to negligible sample size. See Chen et al.[47] for more detail.

Table 2. IPEDS data fields and sources used in these analyses

Variable Name	Variable Description	IPEDS Source
INSTSIZE	Institution Size Category	IPEDS Directory, 2018
LEVEL17	Doctor's degree – research/scholarship	Institutional Characteristics Data File
TUITPL1	Tuition guaranteed plan	
EFASIAT	Asian total	Enrollment in selected major fields of study, by race/ethnicity, gender, attendance status, and level of student: Fall 2018
EFWHIT	White total	
EFTOTLW	Total women	
EFTOLLT	Grand total	
EFCIPLEV	University, All students total	

over time, with members of Cluster 1 holding the next highest GPA, and members of Cluster 3 experiencing the most significant drop in GPA over time (Fig. 1). In summary of our prior work, the four clusters are distinct, only mildly related to the demographics of the participants, and significantly related to success as defined by time-varying GPA.

3.3 Institutional Characteristics

Participants in this analysis came from 14 institutions across the United States. The majority of institutional data were collected from the National Center of Education Statistics (NCES) Integrated Postsecondary Education Data System (IPEDS), a rich data source for institutional characteristics [48]. The remainder of department-level enrollment data came from the American Society for Engineering Education (ASEE) Engineering Data Management System (EDMS). Tables 2 and 3 describe specific IPEDS and EDMS variables and sources for this analysis.

Table 3. ASEE EDMS data fields used in these analyses

Variable Name/Description
White Freshman Sum
White Sophomore Sum
White Junior Sum
White Senior Sum
Asian Freshman Sum
Asian Sophomore Sum
Asian Junior Sum
Asian Senior Sum
Native Hawaiian/Other Pacific Islander Freshman Sum
Native Hawaiian/Other Pacific Islander Sophomore Sum
Native Hawaiian/Other Pacific Islander Junior Sum
Native Hawaiian/Other Pacific Islander Senior Sum
Total Female Enrollment
Total Bachelor Enrollment

Note: EDMS data source: Bachelor's Enrollment by Race and Gender (Institution), 2018.

We chose institutional characteristics based on their potential interactions with student attributes, considered across three categories: (1) that the variable had theoretical bases for potentially interacting with students' NCA profiles (based upon prior literature or researcher experience/intuition), (2) that the variable existed in IPEDS or EDMS and differed across the institutions in the sample, and (3) that the variables were linearly independent.

Overall, the sampled institutions are representative of the national engineering student population (see Table 4). Due to sample size needs for proper statistical power, underrepresented race/ethnic minorities (URMs) were coalesced into a single group in our dataset as well as within the data from IPEDS and EDMS. Particularly, students who did not identify as Asian or White were clustered into this group, as Asian or White students are overrepresented in engineering. Similarly, our initial survey allowed for students to choose multiple gender identities including woman, man, agender, genderqueer, cisgender, transgender, or a write-in response. Because men are historically overrepresented in engineering, and for similar sample size needs for proper statistical power,

Table 4. Institutional and program characteristics obtained through IPEDS and EDMS dataset

School	Large Institution	Doctoral Granting	Tuition Guarantee	Women at Institution [%]	URM at Institution [%]	Women in Engineering [%]	URM in Engineering [%]
A	Y	N	N	26.3	32.6	3.1	31.7
B	Y	Y	N	26	31.4	6.1	31.4
C	Y	Y	Y	31.8	22.3	7	24.4
D	Y	Y	Y	28.6	31.2	18.7	30.3
E	Y	Y	N	31.5	17.6	25.5	17.7
F	Y	Y	N	22.6	31.2	22.8	31.6
G	N	Y	Y	23.9	31.6	—	34.6
H	N	N	N	21	23.7	74.6	22.6
I	Y	Y	Y	27.9	30.1	14	30.2
J	N	Y	N	26.8	31.7	—	33.2
K	N	Y	N	20.8	14.9	32.4	13
L	N	N	N	17.6	15.6	27.9	14.2
M	N	Y	N	14.7	16.8	17.4	16.3
N	Y	Y	Y	20.1	95.4	26.8	94.6

those who did not identify as men were grouped together into a "women or non-binary" group. Both forms of representation are limited by the small numbers of minoritized students in engineering. These processes were statistically appropriate for this work as literature has acknowledged that, though there is variance across different specific groups, there are still broad similarities in experiences of marginalization across underrepresented groups in engineering education [49]. Coalescing these groups gave us the necessary statistical power to properly identify systemic features that impact systematically marginalized students more broadly. Nonetheless we recognize that this process does not completely model the existent inequities many systematically marginalized students face that are typically better represented by qualitative methods such as narrative. This process, which lends itself to the erasure of specific groups (a topic we discuss in work elsewhere; see [50]), remains a limitation of this work as well as quantitative work in engineering education more broadly.

3.4 Participants, Individual Measures, and Institutional Measures

In this paper, we considered only participants who were assigned to a single cluster in our prior work. We therefore excluded from this analysis n = 123 participants who were assigned to more than one cluster, as well as n = 601 unclustered participants. We also excluded participants from institutions with incomplete or missing IPEDS or EDMS data. The final sample used in the present analysis was n = 1,252 participants from 14 institutions. This final sample is a subset of the initial clustered sample with the addition of IPEDS, EDMS, and cluster assignment data.

As shown in Table 5, students at the participating institutions come from varying backgrounds. Mean income, operationalized as average neighborhood socioeconomic status (NSES), was gathered by averaging the 2010 U.S. Census median household incomes associated with students' ZIP codes where they attended high school. This process of linking Census data to estimated students' household income has been documented elsewhere [51] and is considered a best practice in STEM education research [52].

Institutional average ACT scores and overall enrollment were both initially considered as proxies for institutional selectivity [53], but were later removed from the analysis due to possible multicollinearity [according to analysis of variance inflation factor; 54]. Rather, ACT [55] concordance tables were used to transform SAT scores into ACT scores, if ACT scores were not provided (ACT scores were chosen because the majority of institutions in this work reported average ACT scores to IPEDS). The range of percent URM among survey respondents at participating institution ranged from 3.7% – 100.0%, which is similar to the IPEDS and EDMS data for each institution shown in Table 5.

We considered the following institutional characteristics (reference categories for the analysis in parentheses): institution size (Institution Size), doctoral granting (Doctoral Granting), tuition guarantee (Tuition Guarantee), the percentage of women enrolled at the institution (% Women in Inst.), the percentage of women enrolled in engineering (% Women in Eng.), the percentage of traditionally URMs enrolled at the institution (% URM in Inst.), and the percentage of traditionally URMs enrolled in engineering (% URM in Eng.). All continuous

Table 5. Student sample demographics at participating institutions

School	Participants [Count]	Mean Income [$]	Mean ACT [Score]	URM [%]	Women/Non-Binary [%]
A	349	69575	30	18.6	37
B	467	63410	30	13.5	24.6
C	100	56856	29	11	16
D	276	70173	30	17.4	43.5
E	81	62238	31	16	39.5
F	140	64913	26	13.6	31.4
G	228	61294	29	17.5	22.4
H	76	60447	28	6.6	25
I	98	68799	32	16.3	41.8
J	50	65971	27	36	36
K	41	75047	29	17.1	56.1
L	27	53862	27	3.7	29.6
M	111	50361	27	9.9	22.5
N	214	43221	23	93.5	28

variables were standardized ($\mu = 0$, $\sigma = 1$) to allow for model convergence. 'Tuition guarantee' refers to programs at specific institutions in which the tuition for each year of study is guaranteed, in the sense that it is known and predictable, in the student's first year at the institution. Typically, tuition guarantees hold tuition constant throughout a four-year program.

3.5 Multinomial Logistic Regression

In this study, we explore how students from different institutions may be more or less likely to have a particular NCA profile. The intraclass correlation coefficient (ICC), a ratio that identifies how much variance can be explained by the higher-order variables (institution) versus individual level variables, indicated that our data did not have significant variance across these different levels to warrant use of multi-level techniques like hierarchical linear modeling [54]. Similarly, we did not pursue methods such as MANOVA as many of our variables were not categorical in structure (see Table 4).

We used Multinomial Logistic Regression (MLR) to examine how cluster membership may be different based on interactions among institutional and individual characteristics. MLR is a type of logistic regression that allows for multiple categorical outcome variables; here, these outcomes are membership in the four clusters. Within this method, one of the categorical variables serves as a baseline categorical predictor (we chose Cluster 1) by which the other categorical variables (Cluster 2, 3, and 4) are compared [54]. This analysis uses the normative cluster (Cluster 1) as the baseline predictor because it represents the average (in terms of their NCA profile) engineering student while also being the largest cluster [12]. Here, MLR results, like logistic regression results, are reported in odds ratios (ORs); for example, an OR of two would indicate that the odds of being in another cluster versus the baseline cluster are twice as high.

To answer our research question, we built four models of increasing complexity as follows: (1) a control model with only individual variables of survey respondents (URM status, gender, ACT score, and NSES), (2) a model that added both URM and gender percentages at the institutional level (derived from IPEDS) to explore student-institution alignment on demographics, (3) a model that added both URM and gender percentages at the engineering programmatic level (derived from EDMS) to explore student-institution alignment on demographics, and (4) a model that included institutional characteristics (derived from IPEDS) such as institution type (large/small, level of research activity) and the existence of a tuition guarantee, as well as interaction effects between these variables and others in Models 1–4. The control model (Model 1) adds value over our prior work by exploring demographic predictors of cluster membership via a regression approach. In Models 2 and 3, institutional demographics and characteristics were added to the control model one-by-one, adding no new individual variables, and the differences between the previous and new models were compared using an ANOVA. Only variables that generated a statistically significant change in the prediction of cluster membership were considered. After all variables were identified, a new model was created adding in the institutional demographics first to determine their effects. Then the remainder of institutional characteristics were added one-by-one (Model 4). Ultimately, the predictors in the control model were: individual URM status, gender, ACT score, and NSES.

Table 6. Multinomial logistic regression results showing the odds ratios, standard errors in parenthesis, and statistical significance of membership in Clusters 2, 3, and 4 as compared to reference group Cluster 1 for the three models considered here. Model 1 contains only individual–level predictors, Models 2 and 3 include the individual predictors plus a limited set of institutional (Inst) and engineering (Eng) programmatic predictors, and Model 4 contains all individual–level and institutional–level predictors

	Model 1			Models 2 & 3			Model 4		
Predictor	**2**	**3**	**4**	**2**	**3**	**4**	**2**	**3**	**4**
URM status	–1.21 (0.16)	–1.82 (0.22) **	1.43 (0.33)	–1.08 (0.19)	–1.32 (0.23)	1.79 (0.35)	–1.11 (0.19)	–1.31 (0.24)	1.84 (0.35)
Gender	–1.07 (0.13)	–2.07 (0.18) ***	–1.00 (0.29)	–1.07 (0.13)	–2.09 (0.18) ***	–1.00 (0.29)	–1.05 (0.13)	–2.03 (0.18) ***	1.01 (0.29)
ACT	–1.05 (0.07)	1.05 (0.09)	1.06 (0.15)	–1.04 (0.07)	–1.03 (0.09)	1.04 (0.16)	–1.02 (0.07)	–1.01 (0.09)	1.07 (0.16)
NSES	–1.08 (0.07)	–1.17 (0.08)	–1.27 (0.16)	–1.08 (0.07)	–1.22 (0.08) *	–1.31 (0.17)	–1.07 (0.07)	–1.19 (0.08) *	–1.25 (0.16)
Women in Inst.				–1.13 (0.07)	1.11 (0.08)	–1.09 (0.14)	1.15 (0.11)	1.23 (0.13)	–1.19 (0.24)
URM in Inst.				–1.12 (0.08)	–1.41 (0.12) **	–1.26 (0.16)	1.16 (0.12)	–1.22 (0.16)	–1.35 (0.25)
Women in Eng.				–	–	–	–	–	–
URM in Eng.				–	–	–	–	–	–
Institution Size							–2.12 (0.24) **	–1.18 (0.31)	1.33 (0.60)
PhD Granting							1.30 (0.17)	1.80 (0.21) **	2.89 (0.47) *
Tuition Guar.							–1.57 (0.19) *	–1.77 (0.19) **	–1.07 (0.41)
Model Indices									
df		15			21			30	
LRT X^2		38.33			56.09			83.61	
p		<0.001 ***			<0.001 ***			<0.001 ***	
Nagelkerke R^2		0.03			0.04			0.07	

4. Results

In the first model, using individual-level variables as predictors, we found that only URM status and gender, in tandem, were significant predictors of cluster membership (see Table 6). When URM status, gender, ACT score, and neighborhood income were considered together, identifying as a woman or non-binary participant decreased the odds of being in Cluster 3 (Unconnected and Closed Off; OR = –2.07, $p < 0.001$) and identifying as a URM participant decreased the odds of being in Cluster 3 (OR = –1.82, $p = 0.006$).

In the second model, we added the institutional demographic variables (percentage URM and percentage women). Adding these demographic variables resulted in the individual level URM variable dropping out of the model while the institutional URM percentage remained a significant predictor for Cluster 3 (OR = –1.41, $p = 0.005$; see Table 6). This result thus signifies that institutional URM percentage may be more important to consider than individual URM status. Additionally, NSES became significant for Cluster 3 (OR = –1.22, p = 0.019); see Table 6). There was no significant effect to the individual gender variable.

In the third model, we added engineering program variables (percentage URM and percentage women). No new variable was significant leaving Model 3 to be the same as Model 2. These variables were left out of future analysis.

In the final model (Model 4), which included both individual-level variables above and selected institutional characteristics (see Table 6), higher NSES decreased the odds of being in Cluster 3 (OR = –1.19, $p = 0.035$). Students enrolled at large institutions had decreased odds of being in Cluster 2 (High Positive NCA Factors; OR = –2.12, $p = 0.002$) while students enrolled at doctoral granting institutions had increased odds of being in Cluster 3 (OR = 1.80, $p = 0.005$) and Cluster 4 (Without Support from Faculty and Peers; OR = 2.89, $p = 0.024$). Additionally, students who attended universities that offered guaranteed tuition had decreased odds of being in Cluster 2 (OR = –1.57, $p = 0.019$) and Cluster 3 (OR = –1.77, $p = 0.010$). When institutional characteristics were considered, identifying as a member of any race/ethnicity within the URM group was no longer a significant predictor of cluster membership.

To investigate which institutional variable(s) were linked to URM representation among clusters, each institutional variable added to the control model was considered individually and for its interaction with other variables. Including a variable measuring the percentage of URMs in engineering or at the institutional level, or any related interaction, caused the individual variable for URM status to become non-significant in the analysis. Therefore, we found that variance in cluster membership as affected by URM variables may be better explained by institutional characteristics than by individual identities. We see this as a significant finding of this work. Lastly, comparing the final model to the first model using ANOVA, the models were statistically different (df = 15, Likelihood Ratio = 45.28, $p < 0.001$). These findings suggest that institutional characteristics play a significant role over individual characteristics in explaining the variance of cluster membership.

5. Discussion

Based upon this study, we can conclude that individual and institutional variables do indeed interact to predict cluster membership, and that our research question has affirmatively been answered: both *individual* and *institutional* variables play a role in cluster membership prediction, particularly for membership in clusters that are correlated to less desirable student success outcomes [here, our Cluster 3; 12]. The following sections interpret our results in light of specific variables in the analysis.

5.1 University Size and Type

This study significantly advances nascent research linking a suite of NCA factors to institutional type and size. Our hypothesis was that the alignment between individual preferences, expectations, and behaviors and institutional characteristics would manifest in our data as differences in key NCA factors as represented by our clusters. Results of our work indicate that students at large institutions were more than two times less likely to be members of Cluster 2 (OR = –2.12), which is characterized by several factors previously associated with improved academic success and overall wellbeing (e.g., higher motivation, engineering identity, belongingness, gratitude, meaning and purpose, and connection with faculty). Results also show that students at doctoral-granting institutions are more likely to be in Cluster 3 (OR = 1.80) and Cluster 4 (OR = 2.89), both of which are characterized by low scores on factors associated with academic performance, including motivation, engineering identity, belonging, and gratitude. Our consideration of a suite of NCA factors extends prior research that focused on a single or small collection of NCA factors. Our introduction of institutional variables in this analysis adds explanatory power to our prior NCA-factor-only clustering work.

For instance, students at PhD-granting and Master's institutions generally experience lower belongingness than their peers at undergraduate-only institutions [56]. Similarly, Wilson and colleagues [57] found that amongst the larger engineering community, belonging tended to be the lowest for undergraduate students when compared to faculty and graduate students. Belongingness (an individual student NCA factor) is clearly affected by the institutional variables considered here (which may be a proxy for institutional culture). For example, a three-institution study found belongingness and institutional support to be correlated. Specifically, after considering SES, GPA, gender, and several factors related to university characteristics and culture, holistic interpersonal support, which we believe impacts students' NCA success, was found to be the strongest predictor of belonging among both White students and Students of Color [58]. Belonging, aspects of future time perspective motivation, and engineering identity have also been shown to predict engineering student retention [59], a desirable student outcome aligned with the characteristics of our Cluster 2. These results suggest that institutions have an opportunity to deliver student support systems that target multiple NCA factors simultaneously, and that also acknowledge institutional context, to help students build NCA profiles that better align with Clusters 1 and 2. This might mean large institutions could focus on belonging interventions that make large-enrollment campuses feel smaller to students, or that doctoral institutions could expand undergraduate research opportunities to build disciplinary identity and belongingness in a way aligned with institutional mission.

5.2 Traditionally Underrepresented Students in Engineering

5.2.1 Underrepresented Racial/Ethnic Minorities

We gained new insights when we introduced institutional information for demographics as well. In the individual-variable-only analysis (Model 1), students who we identified as URM were less likely to be a member of Cluster 3 (OR = –1.82, $p = 0.006$). Cluster 3 was characterized by low overall scores in many factors associated with student success, so this was a positive result with respect to student outcomes. However, when introducing the institutional characteristics (Models 2 and 3), individual-level URM status became non-significant while the percentage of URM students at the institution became a significant predictor of membership in Cluster 3 (OR = –1.41), a change we suspect is linked to (mis-)alignment between an individual's demographics and those of their institution. The tentatively positive story told by Model 1 (that URM students were less likely to be in Cluster 3) was shifted from an individual consideration to an institutional consideration through the addition of institutional demographics in Model 2. Finally, in Model 4 with the introduction of other institutional variables, all URM-related individual and institutional predictors become non-significant, reinforcing the idea that URM participants in our dataset were equally likely to be a member of any of the clusters.

This result is important for two reasons. First, the Model 4 conclusion that URM students are indeed as likely, statistically, to be in Clusters 2, 3, and 4 as they are to be in Cluster 1 (a less favorable result than that of the control model including individual variables alone) highlights the individual-institutional alignment argument we have mentioned prior. Specifically, while individual characteristics are important, institutional characteristics play a large role in the broader success of students. Model 1 includes only individual-level variables and masks their interactions with institutional variables, yielding an incomplete understanding of cluster membership. While more work needs to be done (see below), we can confirm the counterintuitive outcome that appropriate clustering of individuals relies on information about those individuals *as well as information about their institutions*.

We suspect that this result is also to some extent a function of our dataset, which includes mostly PWI institutions (with several HSIs as well), but no HBCUs. This individual-institutional alignment argument, suggested by our analysis, is also supported by the broader literature [60]. The second reason this result is important is that it further emphasizes the need to enroll participants in future studies from institutions whose missions may better align with their populations. For instance, the institutional-individual question could be explored in much greater depth with the inclusion of HBCUs, two-year institutions, faith-based institutions, and other institution types that are not currently represented in our dataset. This is a clear limitation of this study, and we offer this argument about alignment as preliminary–more work needs to be done. But we believe this work produces significant quantitative insights about individual-institution alignment that stimulate both research- and practice-oriented opportunities as described below.

5.2.2 Women and Non-Binary Students

Women are more likely to enter and complete college, more generally, than men. Relevant to this work, research indicates that women persist in engineering at approximately the same rates as men, even when disaggregated by race [4, 61], and they have higher admissions scores and higher

STEM GPAs than men as well [61–63]. Indeed, the data from this study show that women and non-binary students were two times less likely to be members of Cluster 3 (OR = –2.03, $p < 0.001$) and that this effect was robust in the presence of both individual-level and institution-level variables. This result indicates that women and non-binary students are less likely to be in a cluster with lower indicators for success in engineering, even when accounting for a variety of institutional differences; this result comports with prior literature. This finding is important because of its robustness across institutional characteristics such as size or degree-granting status.

Yet, these findings do not dismiss notions of engineering institutions as gendered organizations which marginalize and exclude women and non-binary students who do not conform to internalized masculine norms [64]. Gendered power structures exist within institutions in many forms that supersede the general characteristics of them [65], such as overall culture and treatment. Literature suggests that these institutional cultures directly impact an individual's help-seeking behaviors, self-esteem, and sexual health [66, 67]. Many of these features are present in engineering [68]. Constructs such as self-esteem have connections to important NCA features such as engineering identity, which is known to predict engineering choice and agency [69]. We believe the institutional characteristics used here may not adequately account for the academic cultures of engineering programs, and this suggests an avenue for further research to explore institutional proxies for culture that can be integrated into this and future analysis.

It is also possible this finding is embedded in the clustering dataset from our prior work [59], wherein we found that women and non-binary students were significantly less represented in Cluster 3. However, even after the introduction of several other individual- and institutional-level controls, the individual gender predictor remained statistically significant. We suspect that the characteristics and cultures of institutions play a greater role in cluster membership than is captured in the models considered here.

5.3 Socioeconomic Considerations

5.3.1 Neighborhood Socioeconomic Status

Recent research suggests that low-income students struggle to feel they belong as engineers because they are perceived as not having socially accepted qualities that engineers are expected to have and exhibit, such as recognized competence and interest in STEM concepts [70–74]. These perceptions are key to one's identification, overall feelings of belonging, and future sense of self as an engineer [75, 76]. Several of these constructs are key features of the clusters explored in this research. For this reason, it is not surprising that students with higher NSES showed lower odds of being in Cluster 3 (OR = –1.19, $p = 0.035$). This result indicates that lower socioeconomic status is indicative of membership in a cluster with lower indicators of success (Cluster 3), even after accounting for institutional differences.

Low-income students' decreased probability of being part of a group with higher positive NCA factors may also connect to systemic resource deprivation. Because students become competent and recognized as mathematicians, scientists, and engineers by participating in relevant activities, students' perceptions of themselves as engineers in college are undoubtedly influenced by their ability to access stimulating STEM activities and resources in college and earlier [74, 51]. However, early access to necessary resources, including parent and teacher support, are not as common (and in many cases, not of sufficiently high quality) in the schools and neighborhoods of low-income students. These systemic deficits are likely due in part to the many overlapping racist, sexist, and classist reasons these neighborhoods and schools remain underfunded. Such effects impact students' choice to enroll and persist in college and engineering [52, 77], likely mediate their perceptions of themselves as engineers, and potentially affect their ability to succeed in engineering [74, 51]. Universities and engineering programs should feel empowered to remedy the resource deficits and in-college strains of socioeconomically disadvantaged students to increase their opportunities to succeed.

5.3.2 Tuition Guarantee

The final institutional model also indicated that the addition of guaranteed tuition decreased the odds of being in Cluster 3 (OR = –1.77, $p = 0.010$). A tuition guarantee ensures that incoming students' tuition costs will not change unexpectedly throughout their enrollment, making predictability of debt easier. The guarantee lessens the chance that a student will be left with additional unplanned out-of-pocket costs when tuition is billed. While tuition guarantees do not solve all socioeconomic equity issues, tuition guarantees still increase the probability that students will be able to plan ahead for how they will pay for their expenses. This increase in probability likely lowers overall student stress allowing students to better focus on success in their studies, a pattern found in a recent financial aid reform study focused on student retention [78]. The report found that tuition guarantees allowed universities to mitigate students' financial risk and stress, or at least their perceptions of it, thus allowing students to focus on their own academic success. A provision of guaranteed tuition likely mitigates engineering students' perceptions of risk while bolstering perceptions of self and potential to succeed. A similar trend has been discussed by Quadlin [6]. It is likely that the final institutional model's incorporation of tuition guarantee referred to this larger psychological assessment of risk.

6. Limitations of Findings

This study has several limitations that prevent the generalizability of the results to all engineering students. First, although data were collected from students at many institutions, and we designed the survey with trustworthiness in mind [42] we simply did not collect or receive data from a sufficiently wide or diverse enough group of students or institutions to enable appropriate analyses at the intersections of demographic groups or institutions. This is an important limitation of the work, given prior work about the importance of intersectional approaches in characterizing students' experiences [79]. A larger sample with greater individual and institutional diversity would support answering our research questions with much greater nuance, and provide much more generalizable conclusions to the community. Similarly, our cluster analysis identified a particularly vulnerable (very low belonging and faculty support) population in Cluster 4, but this population is also small, even given our total sample size. While we consider this work to be an important step along our research trajectory, we fully recognize the considerable room for improvement in our recruitment and sampling procedures. These improvements are being adapted in other parallel projects to that of the present. Finally, our prior use of GMM resulted in a dispersed unclustered group as well as groups who were multi-clustered; the presented analysis contains neither of this groups of students. We recognize that in our work, as with any study, that our results are limited in generalizability. Yet, we believe this work makes an important contribution to the larger body of engineering education research.

A second point of caution regards study measures and data sources. This study is one of the few in engineering education to include SES, specifically NSES, as a variable in the analysis. These data were collected by asking participants for their home ZIP codes and calculating their average neighborhood socioeconomic status from Census data. Although valuable, this approach is limited to a focus on income when research shows that socioeconomic experience goes far beyond the amount of money earned (to include parental education attainment and occupational status, for example), and is drawn from separate, national data sources instead of the participants themselves [71, 80]. We believe NSES is a valuable, if coarse, proxy for socioeconomic status, but clearly further refinements of this approach would add value to future iterations of this study.

7. Implications

7.1 Implications for Research

This research makes an important contribution to studies of student success because it emphasizes the perhaps counterintuitive notion that *clustering of individuals* depends upon the *inclusion of institutional variables.* Using the succession of models presented here, we suggest that alignment of individual and institutional variables plays an important role in cluster membership, which in turn is connected to likelihood of academic success through the NCA constructs composing the clusters. This is an important result because it emphasizes that person-centered analyses need to engage contextual/institutional variables in order to generate a complete picture of cluster membership and the roles of individual-level variables. This important contextual role can be understood in terms of its mediation effect on certain NCA factors, notably identity (recognition), belonging, and perceptions of faculty caring. These constructs all inherently include outside-of-self perspectives (unlike, say, Big Five factors, which are firmly internal to the individual); to the extent that those external perspectives are represented by institutional variables, we should expect them to play a role in this analysis. For instance, the institutional variables related to overall size and level of research activity conspire at large, R1-type institutions to yield a lower perception of faculty caring in general as compared to smaller, teaching-focused settings. Future studies of student success should integrate institutional factors, including proxies for institutional culture, to build more robust models for student outcomes.

7.2 Implications for Practice

This study has implications for individual institutions and for the field overall. These results suggest that, based upon Model 1 using individual variables alone, belonging to an underrepresented group decreases the odds of membership in Cluster 3 (a cluster associated with less favorable outcomes).

This conclusion becomes complicated with the inclusion of institutional characteristics: with the second model, we find that the percentage of URM students at the institution predicts assignment to Cluster 3, while individual URM status becomes non-significant. Adding the remainder of the institutional characteristics leads both individual URM status and the institutional URM percentage to drop from significance, while factors like institution size and the presence of a tuition guarantee become significant. Taken together, these results paint a complex picture; it seems that individual URM status and institutional URM percentage interact in ways this analysis cannot tease apart, but that institutional characteristics carry more weight in individual-level NCA cluster assignments than individual demographics or their interactions alone. This analysis further emphasizes that institutions should support individual students in meaningful ways, but that institutional-level factors (and potentially institutional culture) play a central role in cluster membership and, by extension, student success. These findings support our other prior work developing a consensus model of engineering thriving [81]. Institutions that focus on programmatic support for URM students alone, without an associated commitment to improving the academic culture more generally, may be missing an opportunity to enable their students to achieve greater success [82].

Our results also further reinforce the need for a deeper understanding of socioeconomics and their continuing influence on students. Higher NSES significantly decreases the odds of being assigned to Cluster 3; we suspect that a similar trend would exist from Cluster 4 with a larger population. This observation reinforces research emphasizing long-term effects of socioeconomic disadvantage, in this case producing decreased belonging, identity, and motivation. In contrast, a tuition guarantee at the institution has a conflicting effect on cluster assignment: tuition guarantees are associated with decreased likelihood of belonging to either Cluster 2 or Cluster 3, suggesting more likely Cluster 1 membership (normative cluster).

Finally, most of our results address factors that predict assignment to Cluster 3 versus Cluster 1 (normative group). There are fewer significant predictors for assignment to Clusters 2 and 4, but our findings hold significant implications. Assignment to Cluster 2, the group with the most positive NCA scores, was only predicted by two variables: size of the institution, and presence of a tuition guarantee. Both are reinforced by previous work: students benefit strongly from small class sizes, strong faculty-student relationships, and proactive management of financial concerns. These results urge renewed institutional commitments to help make the complex and often impersonal contexts in larger universities more like smaller institutions. Lastly, assignment to Cluster 4 – characterized by low NCA scores and poor social support – was only predicted by whether the institution was doctoral granting. Although this odds ratio was the highest (2.89), membership in Cluster 4 was the smallest; more research is certainly warranted.

8. Conclusions

Use of clusters and cross-institutional data collection allows for the examination of larger institutional factors that may be masked in studies with smaller samples, and these factors have a significant relationship with students' NCA scores. In our case, clustering allowed for a robust grouping outcome while institutional factors explain a larger amount of variance than individual factors. Future work is needed to further develop and refine our understanding, but these results suggest the existence of complex, nuanced relationships that may be useful inspirations for new institutional practices and supports for engineering students.

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