Research Report

Noncognitive Skill Profiles and Their Relationships With Academic Outcomes at Hispanic-Serving Institutions

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RESEARCH REPORT

Noncognitive Skill Profiles and Their Relationships With Academic Outcomes at Hispanic-Serving Institutions

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Hispanic-serving institutions (HSIs) face a multifaceted set of challenges in determining how to maintain their effectiveness in building student competencies and encouraging their academic success. To understand the importance of noncognitive skills on fostering such success, this study reports on efforts at three HSIs to make meaningful use of noncognitive assessment data in combination with student background characteristics and academic outcomes. We applied a person-centered approach to extract latent profiles from data measuring students' academic skills, commitment, self-management, and social support. These profiles demonstrated reliable patterns of student noncognitive skill expression across the three institutions and exhibited meaningful relationships with external covariates and distal outcomes alike. Suggestions for future research are discussed.

Keywords Hispanic-serving institutions; noncognitive skills; higher education; student success; latent profile analysis

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Concentrating on recent efforts at three Hispanic-serving institutions (HSIs), Holzman and Markle (2018) highlighted potential benefits of focusing institutional attention and resources on noncognitive, or nonacademic, attributes (e.g., inter- and intrapersonal skills) in working with students to support their postsecondary educational success. Their study cited several challenges faced by (but not unique to) HSIs including the provision of postsecondary remedial coursework to academically underprepared students and student stress caused by both a lack of financial resources and family-related demands (Nora & Crisp, 2012; Vasquez-Salgado et al., 2015). Such issues function as structural barriers preventing students' full attention from being devoted to their pursuit of postsecondary education.

One way for institutions to assist students in dealing with such barriers is to support their development and engagement of nonacademic skills with the goal of enabling them to overcome challenges and persist in their education (Habley et al., 2012). In effect, student success at HSIs and higher education in general could be viewed as a combination of the extents to which students are prepared or able to (a) navigate and meet the requirements (both academic and nonacademic elements) of postsecondary environments (Kuh et al., 2006) and (b) obtain holistic supports as needed from the institutions at which they are enrolled (e.g., cocurricular courses or activities, advising/coaching, peer mentors, targeted interventions; Markle & Rikoon, 2018).

In 2017, a research-practice partnership was established between the Hispanic Association of Colleges and Universities (HACU) and Educational Testing Service (ETS). Three HACU member institutions (California State University – Fullerton, Texas State University, and Valencia College – Poinciana) participated in the initial phase of the project. As described in an initial qualitative report, the project's primary objective "was to examine how noncognitive skill information could be infused into student success strategies at HSIs" (Holzman & Markle, 2018, p. 7). Collection and interpretation of information on student noncognitive skill levels at HSIs was aided by their administration of *SuccessNavigator®* (SN), an ETS assessment used in previous research to understand how inter- and intrapersonal factors relate to success in higher education (Markle et al., 2013; Olivera-Aguilar et al., 2017).

The purpose of the current report is to share results from research conducted via the above partnership between HACU and ETS. These results are based on analyses of SN and other data collected at the three participating HSIs. Given the detailed background provided by Holzman and Markle (2018) on HSIs, noncognitive skills, student success in higher education, and key challenges and accomplishments that arose at institutions during the implementation phase of this work, we take the following seven points as granted in presenting the current study.

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1. Noncognitive skills or dispositions play an important role in equipping students to persist through and graduate from postsecondary education.
2. HSIs serve populations of students likely to experience structural or other barriers to success at higher rates versus their majority-group peers.
3. HSIs often cannot resolve or remove such barriers directly.
4. Offering academic and nonacademic support mechanisms can be an effective means of HSIs assisting students in overcoming obstacles they encounter while enrolled.
5. Students attending HSIs are a heterogeneous group whose skill sets and needs are expected to differ.
6. Institutions must thus be prepared to determine each student's strengths and areas of need for further development.
7. Multidimensional assessments can produce reliable, valid, and actionable information HSIs can use to inform the targeted delivery of student supports.

Understanding how students differ from one another with respect to both academic and nonacademic factors is foundational to institutions being able to address specific concerns or difficulties they may be experiencing. Beyond coarse distinctions (e.g., higher scores vs. lower scores), such heterogeneity may also not be readily apparent or reliably distinguished given the large number of student-level data points available to HSIs (student test scores, grades, application or registration information, advising logs, student surveys, etc.). Building off the points mentioned previously and following examples in past research (Olivera-Aguilar et al., 2017; Pastor et al., 2007), in this study we sought to understand student noncognitive skill profiles at three HSIs using data from a standardized assessment instrument (Markle et al., 2013) and applying latent profile analysis (LPA), a person-centered statistical clustering approach using categorical latent variables (Collins & Lanza, 2013). Where different types of outcomes data were available (typically grade point average [GPA] or persistence to subsequent semesters), we also examined relationships between those variables and noncognitive skill profile membership to determine whether such subgroupings also distinguished students from an academic perspective.

Considering each profile in terms of both the attributes defining it and characteristics of its member students was intended to assist HSIs in making data-based decisions (Schildkamp, 2019). Foundational to such efforts is the management, interpretation, and taking of action upon multifaceted data HSIs have at hand (Voorhees & Cooper, 2014). When implemented with rigor, this type of work should enable HSIs to build capacity to make use of key student data (and related analytic findings) in more nuanced and efficient ways than were possible previously.

In the next sections, we describe methodology and results of the current work, detailing the data collected, statistical methods applied, and results obtained with respect to each of the three participating institutions. We then provide an overall summary of findings, attempting to synthesize results across institutional contexts. Finally, we conclude with a discussion of the current study's limitations and suggestions for future research expected to improve our understanding of relationships between noncognitive skills and student success at HSIs.

California State University–Fullerton

Method

Participants

All 1,073 CSUF students represented in our data set were enrolled in the college's first year experience course (University 100). Two thirds of these (65%, $n = 696$) enrolled in the Fall 2017 semester, with 35% ($n = 377$) enrolled in the Fall 2018 semester. Across the entire CSUF sample, students were predominately female (70%). Most identified as Hispanic (58%), with the remainder identifying as Asian (24%), White (9%), international or multiracial (7%), or Black (2%).

Noncognitive Assessment

Students completed the SN assessment during the first 2 weeks of the semester. The assessment has three components: a survey instrument, a series of reports, and a compendium of resources on noncognitive skills. The primary analyses in our study used scores based on the full set of 93 survey questions. The questions targeted four general domains, each of which encompasses two or three specific topics. The domains were Academic Skills (19 items; organization, meeting class expectations), Commitment (17 items; commitment to college goals, institutional commitment), Self-Management (28 items; managing stress, academic self-efficacy, managing test anxiety), and Social Support (29 items; connectedness/sense of belonging, institutional support, lacking structural barriers to success). Student score data at the domain level were used here as input for our LPA models (described in the following paragraphs). Although item-level data were not available in this study, previous research has demonstrated that each domain scale exhibits reliability above $\alpha = .85$ (Markle et al., 2013). To avoid the influence of outliers on LPA model results, values greater than three standard deviations from the mean in each observed score distribution were removed from each domain score variable. Though the observed mean and standard deviation were used in the removal of outliers, in general SN scores are normed with reference to a population distribution with $M = 100$ and $SD = 15$.

Covariates

In addition to SN domain scores, we used variables from two sources as covariates to describe and characterize CSUF students assigned to each latent noncognitive skill profile. Our first source was the background information questionnaire accompanying SN, and the second was deidentified institutional data provided by CSUF. Covariates included in this analysis were the student's gender, high school GPA (HSGPA), parents' level of educational attainment (taking the highest level achieved by any parent), and the extent to which several types of challenges had impacted the student's life in the past year prior to completing SN (e.g., personal problems, financial difficulties, legal issues, family obligations, health issues). The impact of challenges was reported on a 6-point scale from 1 (*no impact*) to 6 (*significant impact*).

Distal Outcomes

Two types of academic outcomes data were obtained from CSUF. The first was overall GPA at the close of the Spring 2018 and Spring 2019 semesters for the Fall 2017 and Fall 2018 cohorts, respectively (i.e., one full academic year after their noncognitive skills were assessed). The second were two binary (yes/no) measures of retention status indicating whether Fall 2017 cohort students remained enrolled at the institution for the Fall 2018 and Spring 2019 semesters, respectively. Although the institution also reported second semester retention (for the Spring 2018 and Spring 2019 semesters for students first enrolled in the Fall 2017 and Fall 2018 semesters, respectively), these rates were essentially invariant (97% and 96%, respectively) and thus not useful as outcomes to distinguish between latent profiles.

Statistical Analysis

LPA is a type of finite mixture model (McLachlan & Peel, 2000) analogous to latent class analysis (LCA) but with continuous indicators (e.g., SN domain scores) supplied as input whereas LCA uses categorical indicators. In the current study, LPA was used to model unobserved heterogeneity in the CSUF sample to reveal previously unrecognized groups of students reporting similar levels of noncognitive skills as one another across the array of four SN domains. As described in Olivera-Aguilar et al. (2017), LPA has advantages over standard person-centered clustering techniques in that it is both model-based (facilitating empirical vs. purely qualitative model selection) and probabilistic rather than deterministic (the former accounting for uncertainty in classification vs. presuming no ambiguity in profile assignment).

M*plus* 8.4 was used to estimate all LPA models presented here, applying robust maximum likelihood estimation (Muthén & Muthén, 2017). Due to the exploratory nature of LPA, where the number of meaningful latent profiles is unknown a priori, multiple models were estimated (retaining two through seven profiles) with fit statistics and profile structures reviewed to determine which model to retain for interpretation and further analysis. From a statistical perspective, models extracting different numbers of profiles were compared using the adjusted Lo–Mendell–Rubin (aLMR) likelihood ratio test; Lo et al., 2001), bootstrap likelihood ratio test (BLRT; McCutcheon, 1987; McLachlan & Peel, 2000), Bayesian information criteria (BIC; Schwarz, 1978), and integrated classification likelihood BIC (ICL-BIC; McLachlan & Peel, 2000). Models were preferred that exhibited lower BIC and ICL-BIC values and p-values greater than 0.05 for the BLRT and aLMR tests (both which compare a model with K profiles to one with K-1 profiles). Understanding that such statistics have a tendency to overextract profiles in LPA and that they may also differ in their indication of which structure is ideal (Nylund et al., 2007; Peugh & Fan, 2013; Tein et al., 2013), we reviewed several additional elements of each model's extracted structure in determining which to retain. These included the proportion of the overall sample assigned to each profile (flagging proportions of approximately 0.05 or lower as potentially unstable) and the qualitative

Table 1 Fit Indices for California State University – Fullerton Latent Profile Analysis (LPA) Models

Profiles	Parameters	BIC	ICL-BIC	aLMR	p_{aLMR}	BLRT	df_{BLRT}	p_{BLRT}	Smallest profile
2	13	34,335.35	33,869.76	681.765	.000	701.305	5	.000	47
3	18	34,194.76	33,459.18	170.594	.000	175.483	5	.000	21
4	23	34,167.63	33,251.33	60.290	.011	62.018	5	.000	12
5	28	34,112.61	33,131.72	87.409	.004	89.914	5	.000	8
6	*33*	*34,106.35*	*32,902.83*	*40.007*	*.020*	*41.154*	*5*	*.000*	*7*
7	38	34,111.36	32,946.28	29.041	.066	29.873	5	.000	3

Note. N = 1,073 for all LPA models. BIC = Bayesian information criteria; ICL-BIC = integrated classification likelihood BIC; aLMR = adjusted Lo – Mendell – Rubin; BLRT = bootstrap likelihood ratio test (BLRT).“Smallest profile” indicates the percentage of the sample assigned to the latent profile with the fewest observations in each solution. Italicized figures indicate the preferred model.

Table 2 Class Sizes and Assignment Probabilities for Six-Profile California State University – Fullerton Solution

Profile	Description	Size (%)	*M* assignment probability
1	Disengaged	7	.84
2	Low engagement, moderate commitment	17	.81
3	Moderate-low	15	.78
4	Strong overall	15	.85
5	Engaged but stressed	25	.73
6	Moderate-high	21	.73

uniqueness of each solution (i.e., whether the extracted profiles were distinctive from one another to the extent they were uniquely interpretable; Pastor et al., 2007).

Once an ideal CSUF profile structure had been selected, we analyzed the same model inclusive of covariates (described previously) entered into a multinomial logistic regression as predictors of latent profile membership. Resulting odds ratios for each covariate were interpreted as the odds of being assigned to each profile relative to a reference profile, given a 1-unit increase in covariate value. This allowed us to characterize the students assigned to each profile according to the covariates described previously while also correcting for classification error in profile assignment (Vermunt, 2010). During the final step in our analysis, we examined relationships between profile assignments and distal outcomes. This was accomplished by estimating the retained CSUF LPA model using an automated three-step procedure (Asparouhov & Muthén, 2014, 2020) where each distal outcome variable was regressed on profile assignments to reveal whether students differed across profiles with respect to their collegiate GPA and retention status. Results of these analyses are reported in terms of standardized effect sizes (d for continuous outcomes such as GPA, h for proportions such as retention; Rocconi & Gonyea, 2018), comparing each pair of two profiles with respect to their average level of a given outcome.

Results

Profile Structure

Table 1 presents model fit statistics for the six LPA models fit to CSUF’s noncognitive assessment data. Although the BLRT suggested extracting additional profiles, the BIC, ICL-BIC, and aLMR statistics converged on a six-profile solution as ideal from a statistical perspective. The six-profile solution was also preferred due to its smallest profile comprising 7% of the overall sample (vs. only 3% in the seven-profile solution). Following the recommendation of Tein et al. (2013), we calculated the Mahalanobis distance (D) between each pair of profiles (15 pairs in all). All values of D were above 2.0, with 60% above 3.0, which were taken to indicate moderate and large amounts of separation between profiles, respectively (McLachlan & Peel, 2000). Figure 1 displays the six-profile structure for CSUF, and Table 2 shows the percentage of the overall sample assigned to each of the six profiles (i.e., profile size) along with mean profile assignment probabilities. Geiser et al. (2006) noted these assignment probabilities can be taken as indicative of the reliability of profile classification. All six profiles in our CSUF solution demonstrated adequate reliability in terms of classification probability, with average values all greater than .70 and most (four of six) near or above .80.

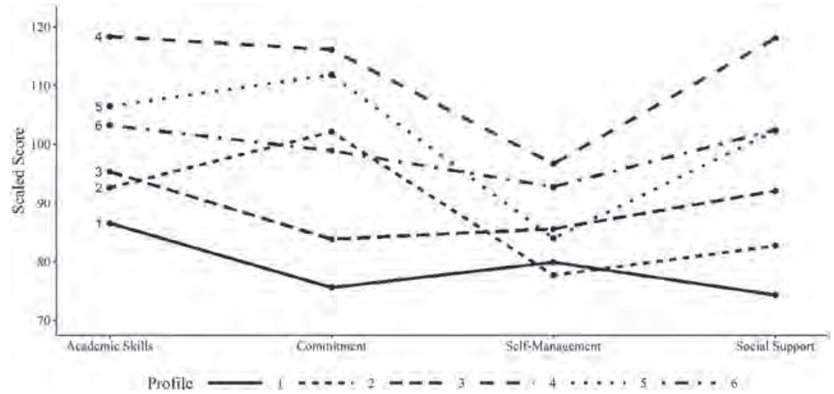

Figure 1 California State University – Fullerton six-profile structure.

Table 3 Odds Ratios for Membership in California State University – Fullerton Profiles 2 – 6 Versus Profile 1

Covariates	Profile 2	Profile 3	Profile 4	Profile 5	Profile 6
Gender	0.341*	0.711	0.555*	0.229*	0.792
HSGPA	0.461*	0.559	0.370*	0.406*	0.365*
Parents' education	0.962	1.110	1.095	1.025	1.099
Personal problems	0.950	0.855	0.718*	0.907	0.835
Financial difficulties	1.030	0.808	0.829	1.064	0.807
Legal issues	1.337	0.683	0.000*	0.839	1.686
Family obligations	0.947	1.108	0.751	0.991	0.901
Health problems	0.859	0.822	0.797	0.807	0.795

Note. HSGPA = high school grade point average. $^{*}p < .05$.

Profile Descriptions

In addition to the statistics described above, Table 2 provides a brief shorthand description for each profile. These were informed by the profile shapes shown in Figure 1 and our analysis of covariate relationships to profile assignment. Results of the multinomial logistic regression of latent profile membership on our set of covariates are shown in Table 3, where odds ratios indicate the predicted change in odds of assignment to Profiles 2 – 6 versus Profile 1 (the reference profile) given a 1-unit increase in each covariate. Students assigned to Profile 1 were more likely to identify as male than in any other profile. Though not shown in Table 3, the prevalence of males ranged from 22% (Profile 5) to 38% (Profile 1). Students in Profile 1 also exhibited higher levels of HSGPA than their peers assigned to other profiles. Although statistically significant in four of five comparisons, actual differences in average HSGPA across profiles were not considered practically meaningful (range 3.60 – 3.66). Parents' level of educational attainment was also similar across profiles, with students in Profiles 1 and 2 slightly less likely to have reported having parents who pursued education beyond the high school level. In general, students reporting higher levels of situational challenges were more likely to be assigned to Profile 1 than to the other five profiles. This was the case for all profiles with respect to personal and health-related problems, with limited exceptions for financial difficulties (Profile 2 and Profile 5), legal issues (Profile 2 and Profile 6), and family obligations (Profile 3) where odds ratios exceeded 1.0 (though generally not to a statistically significant extent) for the comparison to Profile 1. Further description of each profile in terms of its SN domain score levels is found below.

Profile 1 (Disengaged) was distinguished from the others by both being the smallest of the six (7% of the overall CSUF sample) and having demonstrated the lowest average scores in three of the four SN domains. The exception was self-management, where the mean Profile 1 score was statistically indistinguishable from the lowest overall mean score exhibited by Profile 2. The characterization of this profile as "disengaged" is not to suggest that students assigned to it necessarily lack interest in achieving postsecondary success, but their SN scores (particularly low levels of Commitment and Social Support) and greater reported levels of situational challenges were taken to indicate they may have more difficulty engaging in college versus their more committed, connected peers experiencing relatively fewer external challenges.

Table 4 Estimated Grade Point Average (GPA) by California State University – Fullerton Profile and Effect Size (*d*) Differences Between Profiles

Profile	GPA (*SD*)	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	2.93 (1.61)					
2	2.42 (1.51)	0.33				
3	3.34 (0.72)	−0.43	−0.81			
4	2.79 (1.34)	0.10	−0.26	0.57		
5	3.28 (1.56)	−0.22	−0.56	0.09	−0.33	
6	3.05 (2.13)	−0.06	−0.34	0.20	−0.14	0.12

Note. *SD* is estimated based on the standard error (*SE*) of estimated mean GPA and final latent profile counts (n) where $SD = SE \times \sqrt{n}$.

Table 5 Retention to fall 2018 by California State University – Fullerton profile and differences (*h*) between profiles

Profile	Retention	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	0.78					
2	0.89	−0.28				
3	0.85	−0.17	0.11			
4	0.84	−0.14	0.13	0.02		
5	0.93	−0.43	−0.15	−0.26	−0.28	
6	0.85	−0.17	0.11	0.00	−0.02	0.26

Profile 2 (Low Engagement, Moderate Commitment) was characterized by its relatively high level of Commitment (compared to other profiles) combined with lower relative scores in the other three SN domains (Academic Skills, Self-Management, and Social Support). Profile 3 (Moderate-Low) and Profile 6 (Moderate-High) exhibited approximately the same shape, with only quantitative differences in score levels between them (Profile 6 scoring higher across all four SN domains). Differences between these two profiles were most pronounced with respect to Commitment. Profile 4 (Strong Overall) was characterized by exhibiting the highest SN scores in every domain, following the same qualitative score pattern (or profile shape) as found in both Profile 2 and Profile 5 (Engaged but Stressed). The latter profile was the largest of the six (25% of the overall CSUF sample) and showed relatively high levels of Commitment while also exhibiting among the lowest levels of Self-Management. Given that SN scores are based on student self-reports, this pattern suggested students assigned to Profile 5 desired postsecondary educational success but were also relatively less confident than their peers in the extent to which they were able to manage stressful events or persist through obstacles.

Academic Outcomes

Given the tentative nature with which Cohen (1988) proposed interpretive guidelines for d and h (i.e., .20 = small, .50 = moderate, .80 = large) and the typically low magnitude (e.g., $d < .30$) of such effect sizes in educational research contexts (features of which can themselves impact effect size estimates; Rocconi & Gonyea, 2018), we tend to describe such differences here in relative terms (e.g., smaller/larger, lower/higher) rather than applying cutoff-based labels.

Table 4 presents differences with respect to overall collegiate GPA among our CSUF profiles at the end of students' first year of college; Tables 5 and 6 display differences in retention rates to the Fall 2018 and Spring 2019 semesters, respectively, for the CSUF cohort first enrolled during the Fall 2017 semester. First, considering differences in GPA, results were mixed in terms of alignment with what might be expected based on interpretations of students' latent noncognitive skill profiles. For example, whereas Profile 1 might be expected to exhibit the lowest mean GPA and Profile 4 to exhibit the highest, the data showed both in the middle of the overall range (2.42 – 3.34) with only a nominal difference between them ($d = .10$). More in line with expectations was Profile 2, which exhibited the lowest average GPA (2.42) along with its low noncognitive scores in three of the four areas considered. The largest absolute difference, observed between Profiles 2 and 3 ($d = -0.81$), was also difficult to interpret with respect to noncognitive skills scores as both profiles exhibited relatively low average scores in comparison to most other profiles.

Retention results at CSUF were more consistent with expectations based on our interpretations of the institution's noncognitive skill profiles than those related to GPA. As shown in Tables 5 and 6, Profile 1 (Disengaged) experienced

Table 6 Retention to Spring 2019 by California State University–Fullerton Profile and Differences (h) Between Profiles

Profile	Retention	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	0.74					
2	0.87	−0.32				
3	0.86	−0.30	0.03			
4	0.85	−0.26	0.06	0.04		
5	0.92	−0.49	−0.17	−0.19	−0.23	
6	0.83	−0.22	0.10	0.08	0.04	0.27

the lowest rate of retention to future semesters among all six profiles. This finding was particularly pronounced for the further time point (Spring 2019) where retention for Profile 1 was 9% lower ($h = -.22$) than the next lowest profile (Profile 6, Moderate-High). Profile 5 (Engaged but Stressed) exhibited the highest retention rates across both semesters, consistent with its relatively high levels of Academic Skills, Commitment, and Social Support in comparison to other profiles. This finding was also consistent with extant research suggesting a curvilinear relationship between anxiety or stress and task performance (Le et al., 2011). Profile 5 exhibited lower Self-Management versus three of the five other profiles, which may demonstrate the case that moderate (i.e., noncrippling) levels of stress and anxiety focused on academic goals helped to motivate CSUF students in this profile to persist in college.

Texas State University

Method

Participants

The 3,817 first-year TXST students represented in our data set participated in the university's Personalized Academic and Career Exploration (PACE) program during the Fall 2017 semester. Please see Holzman and Markle (2018) for a detailed description of the program and its associated initiatives. As in the CSUF sample, students in our TXST sample were predominately female (70%). Institutional data on students' racial or ethnic identity identified the largest two subgroups as White (43%) and Hispanic (40%), with the next largest subgroup of students identified as Black (12%). Asian students made up 2% of the sample, with an additional 2% identified as international or multiracial. The remaining 1% were identified as belonging to other subgroups.

Noncognitive Assessment

Students completed the same SN assessment as the CSUF students; however, the assessment at TXST was administered during the 1-week orientation period at the beginning of the semester. The same four outlier-corrected domain-level SN score variables (Academic Skills, Commitment, Self-Management, and Social Support) were used as input for our LPA models.

Covariates

As with the CSUF data, covariates used to describe and characterize TXST latent profiles were derived from a combination of institutional data and the SN background questionnaire. The same covariates were included as in our TXST analyses, specifically the student's gender, HSGPA, parents' level of educational attainment, and self-reported impact of five different types of situational challenges over the past year of the student's life.

Distal Outcomes

Three types of academic outcomes data were obtained from TXST. The first two were similar to those obtained from CSUF: overall GPA at the close of the Spring 2018 semester (after one full academic year of coursework) and a binary (yes/no) indicator of retention status indicating whether the student remained enrolled at the institution for the Fall 2018 semester. In addition, TXST provided variables indicating both the credit hours attempted and passed by students. We

Table 7 Fit Indices for Texas State University Latent Profile Analysis (LPA) Models

Profiles	Parameters	BIC	ICL-BIC	aLMR	p_{aLMR}	BLRT	df_{BLRT}	p_{BLRT}	Smallest profile
2	13	122,883.32	121,163.59	2,198.647	.000	2,251.965	5	.000	46
3	18	122,425.63	119,582.50	487.117	.000	498.930	5	.000	18
4	23	122,155.43	118,842.96	304.060	.000	311.434	5	.000	11
5	*28*	*121,950.88*	*117,847.21*	*239.963*	*.001*	*245.782*	*5*	*.000*	*9*
6	33	121,865.08	117,583.77	124.030	.173	127.038	5	.000	5
7	38	121,761.39	117,408.85	141.496	.056	144.927	5	.000	4

Note. $N = 3{,}817$ for all LPA models. BIC = Bayesian information criteria; ICL-BIC = integrated classification likelihood BIC; aLMR = adjusted Lo–Mendell–Rubin; BLRT = bootstrap likelihood ratio test (BLRT). The "smallest profile" column indicates the percentage of the sample assigned to the smallest latent profile in each solution. Italicized figures indicate the preferred model.

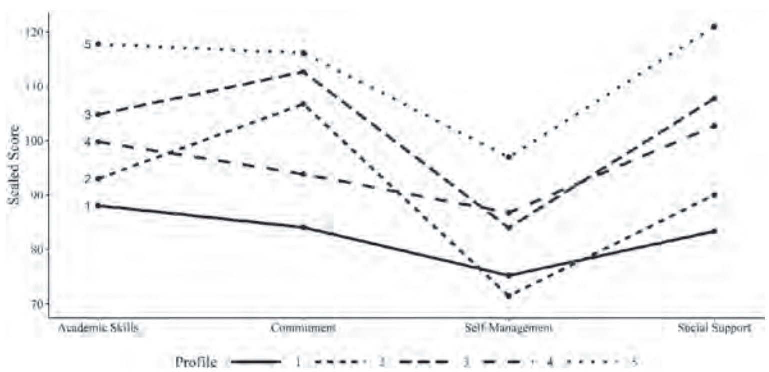

Figure 2 Texas State University five-profile structure.

then calculated a third type of academic outcome indicative of the extent to which a student achieved completion of their planned course load (i.e., the proportion of credits earned, calculated as number attempted/number earned).

Statistical Analysis

All analyses of TXST data followed the same procedures as outlined for CSUF.

Results

Profile Structure

Table 7 presents model fit statistics for the six LPA models fit to noncognitive assessment data from TXST students. Although the BLRT, BIC, and ICL-BIC all suggested extracting additional profiles, the aLMR suggested a five-profile solution would be ideal. A review of class sizes in each solution also suggested a five-profile structure was preferable, with the six- and seven-profile structures each including profiles comprised of 5% or less of the overall TXST sample. In terms of class separation, all D values for the five-profile solution were above 2.0, with 50% (5 of 10) above 3.0 indicating moderate and large amounts of separation between profile pairs, respectively (McLaughlin & Peel, 2000). Figure 2 displays the five-profile structure for TXST, and Table 8 shows the percent of the overall sample assigned to each of the five profiles (i.e., profile size) along with mean profile assignment probabilities. All five profiles in our TXST solution demonstrated adequate reliability in terms of classification probability, with average values all >.70 and most (four of five) above .75.

Profile Descriptions

Table 8 also provides a brief shorthand description for each TXST profile. These were informed by the profile shapes shown in Figure 2 and our analysis of covariate relationships to profile assignment. Results of the multinomial logistic regression of latent profile membership on our set of TXST covariates are shown in Table 9, where odds ratios indicate

Table 8 Class Sizes and Assignment Probabilities for Five-Profile Texas State University Solution

Profile	Description	Size (%)	Assignment probability
1	Disengaged	9	.82
2	Low engagement, moderate commitment	17	.72
3	Engaged but stressed	36	.80
4	Moderate	19	.77
5	Strong overall	20	.77

Table 9 Odds Ratios for Membership in Texas State University Profiles 2 – 5 Versus Profile 1

Covariates	Profile 2	Profile 3	Profile 4	Profile 5
Gender	0.718	0.602*	0.730	0.403*
HSGPA	0.926	1.742	2.479	6.491*
Parents' education	0.986	1.065	1.217*	1.069
Personal problems	0.972	0.797*	0.764*	0.520*
Financial difficulties	1.204*	0.905	0.963	0.829*
Legal issues	0.997	0.939	1.156	0.882
Family obligations	0.960	0.943	0.868	0.887
Health problems	1.034	0.885	0.936	1.038

Note. HSGPA = high school grade point average. $^*p < .05$.

the predicted change in odds of assignment to Profiles 2 – 5 versus Profile 1 (the reference profile) given a 1-unit increase in each covariate. Students assigned to Profile 1 were more likely to identify as male than in any other profile. Though not shown in Table 9, the prevalence of males ranged from 25% (Profile 5) to 37% (Profile 1). Students in Profile 1 were slightly more likely to exhibit a higher HSGPA than their peers in Profile 2, but students in Profiles 3 – 5 were likely to have earned a higher HSGPA than those in Profile 1. As was the case for CSUF, however, actual differences in average HSGPA across profiles were slight (range 3.55 in Profile 2 to 3.67 in Profile 5). Parents' level of educational attainment followed a similar pattern as HSGPA, with parents of students in Profile 2 more likely to have achieved a lower level of education on average versus those of students in Profile 1, whereas parents of students in Profiles 3 – 5 were likelier to have obtained greater amounts of education on average than those in Profile 1. As with the CSUF data, in general students reporting higher levels of situational challenges were more likely to be assigned to Profile 1 than to the other four TXST profiles. This was the case for all profiles with respect to personal problems and family obligations, with limited exceptions for financial difficulties (Profile 2), legal issues (Profile 4), and health problems (Profile 2 and Profile 5) where odds ratios exceeded 1.0 (though generally not to a statistically significant extent) for the comparison to Profile 1. Further descriptions of each TXST profile in terms of its SN domain score levels are found in the following paragraphs.

From a qualitative perspective, student noncognitive skill profiles at TXST exhibited shapes similar to those at CSUF. Profile 1 (Disengaged) was distinguished from the others by being the smallest of the five (7% of the overall TXST sample) and having demonstrated the lowest average scores in three of the four SN domains. The exception was Self-Management, where the mean Profile 1 score was statistically indistinguishable from the lowest overall mean score exhibited by Profile 2. A similar caveat holds here regarding the characterization of this profile as "disengaged." That is, it is not to suggest that students assigned to Profile 1 lack interest in academic success, but instead, that the pattern of their SN scores and greater reported levels of situational challenges indicated they perceived more difficulty engaging in college on average versus their peers.

As with CSUF students, in the TXST data, Profile 2 (Low Engagement, Moderate Commitment) was characterized by its relatively high level of Commitment (compared to other profiles) combined with lower relative scores in the other three SN domains. Profile 4 (Moderate) exhibited approximately the same shape as Profile 1 (Disengaged), but with substantially higher average SN scores across all four domains. Profile 5 (Strong Overall) exhibited the highest SN scores in every domain, following the same qualitative score pattern (or profile shape) as found in both Profiles 2 and 3 (Engaged but Stressed). Again similar to CSUF, the latter profile was the largest of the five at TXST (36% of the overall sample) and showed relatively high levels of Commitment while also exhibiting lower levels of Self-Management.

Table 10 Estimated Grade Point Average (GPA) by Texas State University Profile and Effect Size (*d*) Differences Between Profiles

Profile	GPA (*SD*)	Profile 1	Profile 2	Profile 3	Profile 4
1	2.40 (1.36)				
2	2.93 (1.33)	−0.39			
3	2.74 (1.25)	−0.27	0.14		
4	3.27 (1.13)	−0.72	−0.28	−0.44	
5	3.23 (0.85)	−0.79	−0.27	−0.43	0.05

Note. *SD* is estimated based on the standard error (*SE*) of estimated mean GPA and final latent profile counts (n) where $SD = SE \times \sqrt{n}$.

Table 11 Retention to Fall 2018 by Texas State University Profile and Differences (*h*) Between Profiles

Profile	Retention	Profile 1	Profile 2	Profile 3	Profile 4
1	0.74				
2	0.76	−0.04			
3	0.82	−0.18	−0.14		
4	0.79	−0.12	−0.08	0.06	
5	0.86	−0.30	−0.26	−0.12	−0.18

Table 12 Proportion of Credits Earned by Texas State University Profile and Differences (*h*) Between Profiles

Profile	Proportion	Profile 1	Profile 2	Profile 3	Profile 4
1	0.86				
2	0.90	−0.11			
3	0.91	−0.15	−0.04		
4	0.91	−0.17	−0.06	−0.02	
5	0.93	−0.25	−0.14	−0.10	−0.08

Academic Outcomes

Table 10 presents differences among TXST latent noncognitive skill profiles with respect to overall collegiate GPA at the close of the Spring 2018 semester. Unlike at CSUF, results were generally in alignment with what might be expected based on interpretations of students' latent noncognitive skill profiles. For example, Profile 1 (Disengaged) exhibited the lowest mean GPA by a meaningful margin ($d = -.27$ vs. the next-lowest GPA observed for Profile 3). The largest standardized mean difference ($d = -.79$) was observed between Profile 1 and Profile 5, the latter of which showed the highest noncognitive skills levels in all four domains and was also at the top level of GPA performance (d only .05 from the highest GPA achieved by Profile 4). In the middle of the pack with respect to GPA were Profile 2 ($M = 2.93$) and Profile 3 ($M = 2.74$), which achieved at similar levels to one another ($d = .14$), although one might have expected Profile 3 to perform at a higher level based on each profile's average SN scores.

Table 11 displays differences in retention rates to the Fall 2018 semester between TXST profiles, and Table 12 shows differences in the proportion of credits earned (of those attempted) at the close of the Spring 2018 semester. As was the case with GPA, retention results at TXST were consistent with expectations based on the institution's noncognitive skill profiles. Profile 1 (Disengaged) and Profile 5 (Strong Overall) experienced the lowest (.74) and highest (.86) rates of retention, respectively ($h = -.30$). An interesting pattern of alignment also emerged among all five profiles with respect to two of the four SN domains, where the rank order of retention rates matched that of average SN scores for both Academic Skills and Social Support. Approximately the same pattern of results for retention was found in terms of the proportion of credits earned (Table 12), although differences in this area could be considered less practically meaningful than those for retention for several reasons. First, retention represents a more absolute outcome for students. Moreover, students in all TXST profiles earned an overwhelming majority of their attempted credits on average, and the range of earned credit proportions was narrower overall (.86 for Profile 1 to .93 for Profile 5, $h = -.25$) versus that of retention rates.

Valencia College–Poinciana

Method

Participants

The 320 VCP students represented in our data set were all enrolled in the institution's new student experience (NSE) course in either the Spring 2018 ($n = 160$) or Fall 2018 ($n = 160$) semester. As was the case at the other two institutions, overall a majority of the VCP identified as female (62%). A similarly sized majority (62%) identified as Hispanic, with the next largest subgroup of students identifying as Black (18%). White students made up 10% of the sample, with an additional 3% identifying as Asian and the remaining 8% belonging to less prevalent subgroups or electing not to specify a racial or ethnic identity.

Noncognitive Assessment

Students at VCP completed the same SN assessment as did CSUF and TXST students, however at VCP students were permitted to complete the assessment at any convenient point during their semester of enrollment in the NSE course. The same four outlier-corrected domain-level SN score variables (Academic Skills, Commitment, Self-Management, and Social Support) were used as input for our VCP LPA models.

Covariates

As was the case for the other two institutions, covariates used to describe and characterize VCP latent profiles represented a combination of data provided by the institution and the SN background questionnaire. The same covariates were used as at CSUF and TXST, including the student's gender, HSGPA, parents' highest level of educational attainment, and self-reported impact of situational challenges over the past year of the student's life.

Distal Outcomes

Two types of academic outcomes data were obtained from VCP, similar to those at the other two institutions. The first was overall GPA at the close of the semester in which students completed their NSE course. In addition and similar to TXST, we were able to calculate the extent to which VCP students completed their planned course load (i.e., the proportion of enrolled credits earned by the close of the semester). Enrollment status to the following semester or academic year (i.e., retention) was not available for students in our VCP data.

Statistical Analysis

All analyses of VCP data followed the same procedures as outlined for CSUF and TXST.

Results

Profile Structure

Table 13 presents fit statistics for LPA models fit using SN data from VCP students. In this case, the statistics pointed to two different models as being potentially ideal. A five-profile structure was indicated by both the BLRT and ICL-BIC, whereas the aLMR and BIC suggested a three-profile structure should be retained. Reviewing class sizes in each solution led to a preference for the three-profile structure. Although the smallest profile size in the five-profile structure appeared acceptable at 9%, the relatively small overall $N = 320$ in our VCP sample implied that smallest profile would be based on only $\sim$29 observations. The smallest profile in the three-profile structure (24%) contained $\sim$78 observations and was thus considered more stable in terms of its likelihood of replication in future research. In terms of class separation, all D values for the three-profile VCP solution were above 2.5 (with one of three above 3.0), adequate amounts of separation between profile pairs. Figure 3 displays the three-profile structure for VCP, and Table 14 shows the percent of the overall sample assigned to each of the three profiles (i.e., profile size) along with mean profile assignment probabilities. All three profiles in the VCP solution demonstrated high levels of reliability in terms of classification probability, with average values all $>.85$.

Table 13 Fit Indices for Valencia College – Poinciana Latent Profile Analysis Models

Profiles	Parameters	BIC	ICL-BIC	aLMR	p_{aLMR}	BLRT	df_{BLRT}	p_{BLRT}	Smallest profile
2	13	10,616.97	10,485.22	176.526	.000	182.646	5	.000	35
3	*18*	*10,561.78*	*10,371.94*	*81.212*	*.000*	*84.028*	*5*	*.000*	*24*
4	23	10,564.64	10,342.83	25.107	.125	25.977	5	.000	9
5	28	10,570.26	10,276.70	22.444	.168	23.222	5	.000	9
6	33	10,583.44	10,281.85	15.145	.224	15.670	5	.109	7
7	38	10,601.59	10,321.38	10.328	.594	10.686	5	.667	3

Note. $N = 320$ for all LPA models. BIC = Bayesian information criteria; ICL-BIC = integrated classification likelihood BIC; aLMR = adjusted Lo – Mendell – Rubin; BLRT = bootstrap likelihood ratio test (BLRT). The "smallest profile" column indicates the percentage of the sample assigned to the smallest latent profile in each solution. Italicized figures indicate the preferred model.

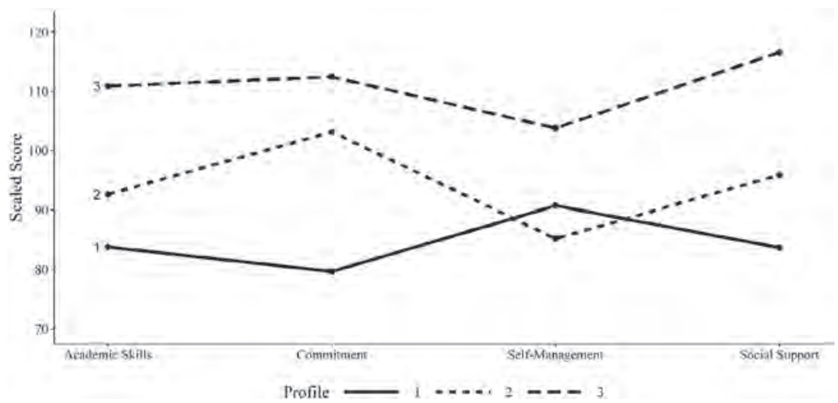

Figure 3 Valencia College – Poinciana three-profile structure.

Table 14 Class Sizes and Assignment Probabilities for Three-Profile Valencia College – Poinciana Solution

Profile	Description	Size (%)	Assignment probability
1	Disengaged	25	.88
2	Committed but stressed	51	.88
3	Strong	24	.87

Profile Descriptions

Table 14 also provides a brief shorthand description for each VCP profile. As was the case for CSUF and TXST, these descriptions were informed by the profile shapes shown in Figure 3 and an analysis of covariate relationships to profile assignment. Results of the multinomial logistic regression of latent profile membership on the set of VCP covariates are shown in Table 15, where odds ratios indicate the predicted change in odds of assignment to Profiles 2 and 3 versus Profile 1 (the reference profile) given a 1-unit increase in each covariate.

Again similar to the other two institutions, students assigned to Profile 1 were more likely to identify as male than in any other profile. Though not shown in Table 15, the prevalence of males ranged from 34% (Profile 2) to 49% (Profile 1). Differences in average HSGPA across latent profiles were so slight as to be functionally nonexistent at VCP, ranging from 2.98 in Profile 2 to 3.00 in Profile 1. Differences in parents' level of educational attainment were slight as well, although students in Profile 2 reported their parents achieved a lower level of education on average versus those of students in Profile 1, whereas parents of students in Profile 3 were likelier to have obtained a greater amount of education on average than those of students in Profile 1.

Experiences of situational challenges were mixed across the three profiles. Students in Profile 2 reported having experienced higher levels of personal and health problems as well as legal obligations versus those in Profile 1, whereas students

Table 15 Odds Ratios for Membership in Valencia College – Poinciana Profiles 2 – 5 Versus Profile 1

Covariates	Profile 2	Profile 3
Gender	0.300*	0.233*
HSGPA	0.556	0.466*
Parents' education	0.962	1.049
Personal problems	1.173	0.707
Financial difficulties	0.970	0.829
Legal issues	0.685	1.154
Family obligations	1.090	1.116
Health problems	1.012	0.926

Note. HSGPA = high school grade point average. $^{*}p < .05$.

Table 16 Estimated Grade Point Average (GPA) by Valencia College – Poinciana Profile and Effect Size (d) Differences Between Profiles

Profile	GPA (*SD*)	Profile 1	Profile 2
1	2.63 (1.31)		
2	2.51 (1.16)	0.10	
3	3.12 (0.70)	−0.47	−0.59

Note. *SD* is estimated based on the standard error (*SE*) of estimated mean GPA and final latent profile counts (n) where $SD = SE \times \sqrt{n}$.

in Profile 3 were more likely to report having experienced legal issues and family obligations versus their Profile 1 peers. Financial difficulties were experienced by students in Profile 1 with greater prevalence than students in either of the other two profiles. Further description of each VCP profile in terms of its SN domain score levels is found below.

Though there were fewer of them, the three noncognitive skill profiles at VCP exhibited similar shapes to their analogous counterparts at the other two institutions. Profile 1 (Disengaged) was distinguished from Profiles 2 and 3 by having demonstrated the lowest average scores in three of the four SN domains (all except self-management). VCP students assigned to Profile 2 (Committed but Stressed) were characterized by their relatively high level of Commitment combined with lowest relative average score on Self-Management. Although VCP's Profile 2 exhibited the same general shape as the Engaged but Stressed profile found using data from the other two institutions, in VCP's case only the mean score for Commitment rose above the national $M = 100$ level. At both CSUF and TXST the analogous profile was above the national average on three of the four SN scales, indicating broader self-reported engagement with postsecondary education relative to their peers versus Profile 2 in the VCP solution. Profile 3 (Strong) exhibited the highest SN scores in every domain by a meaningful margin versus the other two profiles, following the same qualitative score pattern as the analogous profile at both CSUF and TXST (though with a less extreme dip in Self-Management).

Academic Outcomes

Table 16 presents differences among VCP latent noncognitive skill profiles with respect to their average GPA at the close of their NSE course semester (either Spring 2018 or Fall 2018). Profile 3 (Strong) exhibited the highest mean GPA by approximately 0.5 *SD* in comparison to each of the other two profiles. Although one might have expected Profile 2 to demonstrate a substantially higher GPA versus Profile 1 given observed differences in the two SN score profiles, we observed only a nominal difference between them ($d = .10$).

Table 17 shows differences between VCP profiles in their average proportion of credits earned (of those attempted) at the close of the NSE course semester. These results were consistent with those for GPA in two respects. First, students assigned to Profile 3 (Strong) earned a substantially greater proportion of attempted credits versus those in the other two profiles. Second, the difference on this metric between Profile 1 and Profile 2 was smaller than that of either's difference with Profile 3. As was the case for TXST, students in all VCP profiles earned a large majority of their attempted credits on average.

Table 17 Proportion of Credits Earned by Valencia College – Poinciana Profile and Differences (h) Between Profiles

Profile	Proportion	Profile 1	Profile 2
1	0.85		
2	0.80	−0.13	
3	0.95	0.33	0.46

Discussion

As discussed by Núñez et al. (2015), HSIs as a broad set of institutions tend to face a series of compounding challenges. First, they serve subgroups of students more likely than their peers on average to lack access to both the economic and social capital resources supportive of success in higher education (traditionally defined as persistence to graduation). Second, HSIs themselves tend to possess fewer resources than non-HSIs to provide students with the types of support (economic and otherwise) that research has shown can help them achieve postsecondary success (Núñez et al., 2015). Key to this discussion is how success is conceptualized with respect to HSIs, either traditionally as limited to retention and graduation rates, or more holistically including explicit attention to the extent to which HSIs foster the development of students' complex set of talents and competencies such as civic engagement, self-confidence, etc. (Hurtado & Alvarado, 2015). Understanding these types of nonacademic characteristics are foundational to promoting student success in higher education (Burrus et al., 2013); prerequisite to their consideration and evaluation as either developmental milestones or student outcomes is the collection and availability of fair (i.e., comparable across students) and reliable information. Acquiring such data at the level of distinguishable constructs usually requires some form of targeted assessment strategy (Kyllonen, 2016; Markle & Rikoon, 2018).

Although the current study lacked long-term data on graduation status, our analysis attempted to bridge both perspectives on student success above using data from students' first postsecondary year as early indicators of their progress. In collaboration with a diverse set of three HSIs, we collected data on a multidimensional set of noncognitive characteristics using an established instrument (Markle et al., 2013) in combination with both student background attributes and academic outcomes (e.g., GPA, credit accrual, retention). Latent profiles extracted from the data revealed multiple reliable patterns of student noncognitive skill expression. These tended to be qualitatively consistent across institutions, with some consistency as well in how profile membership was related to available outcomes data.

With respect to profile structure, two patterns of noncognitive scale scores tended to stand out. The first was characterized by relatively higher scores on Commitment but substantially lower scores on Self-Management. Although it is inappropriate to compare quantitative score levels between domains (e.g., scores of 110 on Commitment and 95 on Self-Management do not imply a student has "more" of the first domain than the second), we found a steady pattern of students rating themselves relatively higher with respect to their nationwide peers on commitment while also rating themselves lower with respect to their ability to self-manage through difficult experiences. This could be reflective of students in these profiles acknowledging or demonstrating that some amount of stress and anxiety serve to motivate performance (Le et al., 2011; Wang et al., 2015). The other consistent type of profile structure was one of relatively similar scores across all four SN domains (e.g., Moderate and Disengaged profiles). With limited exceptions, on average students in the Disengaged profiles tended to perform at the lower end of each institution's academic outcomes distributions.

We also found some consistency across institutions with respect to covariates describing the backgrounds of students making up each latent profile. Males were more likely to demonstrate noncognitive characteristics aligned with the Disengaged profile versus other profiles in pairwise comparisons across each selected LPA model. At CSUF and VCP, a similar trend held true for HSGPA, with students in the Disengaged profile exhibiting lower levels of prior academic achievement on average versus peers assigned to other profiles at each institution. Results concerning the extent to which students reported experiencing five types of situational challenges were generally in the same direction but more mixed, with 16%, 25%, and 50% of comparisons between the Disengaged profile and others at CSUF, TXST, and VCP, respectively, showing that students in the former subgroup experienced higher levels of such challenges relative to peers in other profiles.

The only academic outcome available across all three institutions was GPA, where students assigned to latent profiles with lower average noncognitive scores also tended to earn lower GPAs on average. An exception here was at CSUF, where the Strong Overall profile exhibited the second-lowest GPA among the six retained profiles. Although we lacked data sufficient to explore this anomaly further, one avenue for future research is to examine patterns of course taking among students in each profile that may help explain observed GPA differences (e.g., certain profiles may engage in more difficult coursework vs. others). Considering retention to future semesters (arguably a more important practical outcome for both students and institutions vs. GPA), at both institutions where figures were available, students in the Disengaged profile tended to be retained at the lowest rates. Students in the Strong profile were retained at the highest rates at TXST (where they also earned the highest proportion of attempted credits among all profiles), whereas at CSUF, retention results for the Strong Overall profile were mid-range (similar to GPA). Proportion of credits earned appeared to be more meaningful at VCP than the other two institutions, where this statistic exhibited a wider range and larger differences between profiles than at TXST.

Results of this study could be built upon in future research to test several potential benefits that institutions may accrue through the holistic consideration of student noncognitive skills measured using reliable and valid assessment data. For example, HSIs could use noncognitive assessment data with clustering methods such as LPA to identify previously unobserved subgroups of students that may benefit from interventions targeting specific constructs (Hickendorff et al., 2018). In this way, an institution's limited resources could be used more efficiently than may be possible at present. Longitudinal studies applying similar methodology (e.g., latent transition analysis) should also be conducted to assess the stability (or instability) of profile structures over time as students progress through postsecondary education. Learning the specific ways in which students' noncognitive skill levels may shift as they approach transitioning to the workforce may help HSIs address current skills gaps perceived by employers (Cunningham & Villaseñor, 2016). A significant opportunity also exists to use modern technology to gather more intensive longitudinal data on student perceptions and noncognitive characteristics, offering the potential to enhance our understanding of how students deploy such capacities on increasingly granular time scales (e.g., day to day) to meet the challenges of higher education (Goetz et al., 2010; Manwaring et al., 2017; van Berkel et al., 2017).

The primary limitation of our study is that it was limited to only three participating institutions, with each participating in the study independently of the others. That is, each delivered the noncognitive assessment and any related support mechanisms to meet institutional objectives as opposed to in close coordination with one another (Holzman & Markle, 2018). While this approach was optimal from a practical perspective given the variety of institutional contexts and goals at hand, without a substantial number of additional HSIs conducting similar studies our findings cannot be generalized beyond the three examined here. Future work of this kind should be conducted at a wider array of HSIs to demonstrate its applicability more broadly.

Another limitation is found in the data available to this study. Although we had access to both personal background and outcome variables, it would have been ideal, particularly with respect to outcomes, to study a wider range than those purely academic in nature (e.g., students' leadership experiences, graduating major, field of eventual employment, on-campus service utilization; Robbins et al., 2009). This gives rise to the recommendation that HSIs and other institutions exert considered effort prior to engaging in such work to determine which constructs and outcomes in the noncognitive space are of greatest interest and in alignment with their missions—a particularly key set of distinctions given debate in the field about how to define and operationalize constructs in the noncognitive space (Markle & Rikoon, 2018; Rowan-Kenyon et al., 2017). Such debate should also be considered an opportunity, however, to broaden our typical consideration of what types of variables are considered meaningful student outcomes. In particular for those who may not achieve traditional metrics of success (e.g., degree attainment) for reasons that may be outside their personal control, as noted above (Hurtado & Alvarado, 2015), HSIs and other educational institutions can play a role in fostering student development toward competencies that should improve the likelihood of their success in life regardless of any specific educational outcome.[1]

This study has characterized student noncognitive attributes at three HSIs, demonstrating the utility of standardized assessment data for considering nonacademic constructs using a holistic, person-centered approach (LPA). We have also demonstrated meaningful relationships (in both anticipated and unexpected directions) between noncognitive skill profiles and student academic outcomes, suggesting ways in which the profile structures retained in this study may be used both institutionally and in future research. Although the current work has built upon existing studies to illustrate how students' nonacademic skills present in concert with one another at HSIs, the field should also look forward to further insights gained from advanced analytic techniques (Daniel, 2017). Such advances are already augmenting and integrating data from both cognitive and noncognitive assessments, institutional records, learning experiences, and more to generate novel findings and personalized learning experiences in service of fostering student success.

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Note

1 Similar calls to broaden the outcomes space with respect to noncognitive variables have also been made in K12 education (e.g., Hart et al., 2020).

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