Board 98: Validity Evidence for the SUCCESS Survey: Measuring Non-Cognitive and Affective Traits of Engineering and Computing Students (Part II)

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

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Abstract

This IUSE (Improving Undergraduate STEM Education) NSF (National Science Foundation) grantee poster describes our work deploying a national survey (the SUCCESS survey—Studying Underlying Characteristics of Computing and Engineering Student Success) to collect data on students' non-cognitive and affective (NCA) factors. This survey, which is the first of its kind to be launched on a national scale, measures 28 NCA factors that may contribute to student success including personality, grit, identity, mindset, motivation, stress, gratitude, mindfulness, and belongingness. Many engineering and computing students have strong incoming academic records and standardized test scores that indicate potential for success in their programs; nonetheless, many struggle when they reach university. Cognitive measures like SAT/ACT are weak predictors of academic success, and NCA measures may form the constellation of characteristics that offer further predictive power. In this paper, we present construct validity evidence from a confirmatory factor analysis for the SUCCESS survey using a national sample of n = 2672 students, as well as findings from our think-aloud interviews to support face validity. Through confirmatory factor analysis, we removed several items from our survey that did not load onto factors as expected thus improving the measurements and reducing survey length. In addition, the think-aloud interviews allowed us to adjust the wording of questions and to add further demographic options to the survey. Our future work includes using cluster analysis to develop non-cognitive profiles of our participants. We will also use our national dataset to develop predictive models for student success, defined in both academic (e.g., GPA, etc.) and non-academic terms.

Introduction

Many engineering and computing students have strong pre-college academic records that indicate potential for success in their programs; nonetheless, many struggle when they reach the university setting. Cognitive measures like SAT/ACT are at best weak predictors of academic success [1], [2], and non-cognitive and affective (NCA) measures may form the constellation of characteristics that offer further predictive power [3]. This IUSE NSF grantee poster describes our work to date to collect data on students' NCA factors using the SUCCESS survey—Studying Underlying Characteristics of Computing and Engineering Student Success. The survey uses constructs such as big five personality, future time perspective (motivation), engineering identity, belongingness, gratitude, and others. In this paper, we present validity evidence from a confirmatory factor analysis for the SUCCESS survey using a national sample of n = 2672 students, as well as findings from think-aloud interviews to support face validity. We have collected survey data from 17 ABET accredited institutions; at three of these institutions, we are also collecting registrar and dean-of-students records for an even deeper examination of how NCA factors may play a role in overall student success.

Methods

Survey Administration: Throughout the 2017-2018 academic year, we developed [4] and administered the SUCCESS survey and collected 3,746 total responses from 17 institutions. After cleaning (removing responses which failed an attention check embedded toward the end of the survey or incomplete surveys), 1074 responses were removed, resulting in a total of $n = 2672$ responses. This survey was focused on measuring non-cognitive and affective factors, taken from existing instruments used with similar populations, that have the potential to predict engineering and computing student success [5]. This survey measures 32 NCA factors that may contribute to student success including personality, grit, identity, mindset, motivation, stress, gratitude, mindfulness, and belongingness, and is the first of its kind launched on a national scale. We use the results of this survey instrument in the confirmatory factor analysis we present (CFA).

Confirmatory Factor Analysis: In the Summer of 2017, we launched a pilot survey to determine if our survey measures showed evidence of validity ($n = 490$). Using that data, we conducted exploratory factor analysis (EFA) [5] and found some measures that did not have strong validity evidence, which led to the exclusion of two constructs and over 50 survey items, resulting in the survey administered and discussed within this paper.

Unlike EFA, CFA assumes that all relationships between items and latent factors are known. For CFA, the relationships among items are determined *a priori*, with all items loading onto specified factors [6]. The relationships across factors are also determined. For our analysis, we used the *cfa()* function [7] in R [8] using a maximum likelihood estimator (due to our data being non-normal with excess skew and /or kurtosis) [9], [10] with a Satorra-Bentler correction (used to correct for non-normality). Prior to CFA, we imputed missing data using Full Information Maximum Likelihood from the *amelia()* function [11]. We used the results of the EFA as the initial factor structure to test within CFA.

Next, we examined the loadings and fit within the CFA models. After each CFA model was generated, we checked to ensure that the tested relationships were significant ($p < 0.05$). We then checked to ensure that all of the factor loadings are greater than 0.6 [12]. Further, we used a cutoff of 0.5 for average variance extracted (AVE) for each factor, with low AVE generally meaning the variance explained by the construct is lower than measurement error [13]. We also considered composite reliability (CR > 0.7) which is related to the overall consistency of a measure [14]. Additionally, we ensured that the factors were unique through discriminant validity (DV), ensuring that the squared correlation among factors is less than the AVE from a given pair of factors [15].

Once the above conditions were met, we considered the fit indices. In CFA several fit indices are employed including: Tucker Lewis Index (TLI > 0.9), Composite Fit Index (CFI > 0.9), Root Mean Square Error of Approximation (RMSEA < 0.08), and Standardized Root Mean Squared (SRMR < 0.05). While these are not inclusive of all potential fit indices, they are considered to be the most widely accepted [16] and are the ones we adopted. We initially performed CFA on a per-construct level, ensuring that the loadings, AVE, CR, and DV met the cutoffs described above. In the event of potentially different models to test (e.g., grit as an overall factor instead of grit being represented as the two factors of consistency of interest and perseverance of effort), we relied on fit indices to guide overall model specification. Once CFA was completed on individual constructs, all potential factors were combined to analyze together.

Think-aloud Interviews*:* The research team, comprised of instructors of practice in large departments (computer science, first-year engineering, and mechanical engineering), provided an initial round of review for the face validity of survey items. Their judgements of item interpretability were informed by their experiences, as well as their knowledge of the research concerning non-cognitive and affective factors.

However, faculty were not the target audience for the survey. So, we also conducted think-aloud interviews with students as they took the survey to determine how they interpreted the survey, which provided a second measure of the survey's face validity [17]–[19]. We used the feedback from the interviews to confirm that the interviewees interpreted the survey items as intended, even if English was not their native language. Three interviews were conducted and transcribed for review. Two of the three interviewees were international students, one of whom had been at the university for one year while the other had been there for three years. The third interviewee was a third-year native-born American student.

Results

We collected data from Oct. 2017-June 2018 according to the procedures outlined above. As shown in Table 1, the majority of the factors pass discriminate validity checks, but several do not. In order to ensure that all items measure different constructs (have discriminate validity), we examined factors that were both mathematically and conceptually related. If factors were highly correlated and therefore did not discriminate from one another, we removed the factor with the lower AVE, or combined factors into a single construct, as applicable. We removed: Engineering Identity Performance Competence because its AVE was lower than Motivation Expectancy, 0.613 and 0.737 respectively; Self-Control Restraint because its AVE was lower than Self-Control Impulsivity, 0.423 and 0.433 respectively; and Academic Support because its AVE was lower than Empathetic Faculty Understanding, 0.436 and 0.545 respectively. Instead of unique fixed and growth mindset, we used a factor structure that combined them into an overall mindset measure, where scoring higher means more growth than fixed mindset [20]. This process of factor elimination or combination reduced the set of 32 factors in Table 1 down to a total of 28 NCA factors. The fit indices for the combined model (as shown in Table 1) are as follows: CFI = 0.935, TLI = 0.928, SRMR = 0.034, and RMSEA = 0.028 (90% CI 0.027/0.028). These values meet our imposed fit indices, as described earlier.

Table 1. CFA results considering all factors together.

	Max r^2	**AVE**	**DV**	**CR**
Neuroticism	0.225	0.653	PASS	0.846
Extraversion	0.127	0.659	PASS	0.853
Agreeableness	0.124	0.576	PASS	0.799
Conscientiousness	0.299	0.514	PASS	0.760
Openness	0.135	0.576	PASS	0.801
Consistency of Interest	0.282	0.443	PASS	0.760

	Max r^2	AVE	DV	CR
Meaning and Purpose	0.165	0.748	PASS	0.899
Engineering Identity Interest	0.647	0.780	PASS	0.914
Engineering Identity Performance Competence	0.676	0.613	FAIL	0.887
Engineering Identity Recognition	0.351	0.545	PASS	0.824
Motivation Expectancy	0.676	0.737	PASS	0.933
Motivation Connectedness	0.082	0.507	PASS	0.804
Motivation Instrumentality	0.449	0.739	PASS	0.894
Motivation Value	0.042	0.658	PASS	0.792
Motivation Perceptions of Future	0.650	0.684	PASS	0.896
Fixed Mindset	0.690	0.677	FAIL	0.893
Growth Mindset	0.690	0.730	PASS	0.915
Time Management	0.346	0.406	PASS	0.731
Test Anxiety	0.291	0.566	PASS	0.838
Social Support	0.508	0.832	PASS	0.908
Academic Support	0.551	0.436	FAIL	0.605
Empathetic Faculty Understanding	0.551	0.545	FAIL	0.826
Self-Control Impulsivity	0.464	0.433	FAIL	0.752
Self-Control Restraint	0.464	0.423	FAIL	0.686
Stress Frustrations	0.280	0.528	PASS	0.769
Stress Conflict	0.172	0.526	PASS	0.766
Stress Changes	0.280	0.721	PASS	0.886
Stress Reactions	0.291	0.572	PASS	0.799
Stress Support	0.124	0.533	PASS	0.695
Gratitude	0.368	0.622	PASS	0.867
Belonging	0.650	0.780	PASS	0.934
Mindfulness	0.221	0.661	PASS	0.886

Through the think-aloud interviews, we learned that the interviewees did experience some confusion and frustration while taking the survey. Some incidents were structural to the survey and easily correctible (e.g., a missing major) while others were interpreted as being natural to survey tools (e.g., a feeling of repetitiveness) and simply noted. Some were specific to the wording of some survey items but could or should not be changed since these items were taken from a validated survey (e.g., “does ‘frequent mood swings’ refer to something out of one’s control while ‘change my mood a lot’ mean I have control over it?”). While most confusion of this type occurred with international students, the American student also experienced some of these issues as well. A final type of confusion, almost exclusive to international students, was wording specifically referencing American culture, such as “K-12”, “faculty” vs. “faculty member” (and who is included in this category). Where possible, we have worked to make wording as inclusive as possible and to apply to a broad range of student experiences in U.S. universities.

Discussion/Conclusion

These validity analyses allowed us to remove 31 items from our survey in conjunction with six factors. This contraction reduced the cognitive load on the students taking our survey by reducing time to completion. We also added three additional items to the survey demographic questions and changed the wording of some of the demographic questions to be more easily interpretable by our participants and provide additional options. Overall, we learned that using items that have validity evidence with a general population does not necessarily translate to validity in an engineering population. For example, consistent with recent work [21], grit does not show validity evidence across the engineering population. We have since launched a revised version of this survey with the updates from this analysis.

So far in this project we have developed a national survey that explores NCA factors that could have potential for predicting engineering and computing student success [22]. We have used our pilot data to show that NCA factors explain an additional 20% of variance in college GPA after controlling for ACT/SAT scores and several demographic factors [3]. We are currently using clustering techniques to identify different groups of engineering students based on NCA factor responses. Future work will explore how these clusters can be used as predictors for other measures, as well as institutional differences among student populations.

Overall, our future work contributes to broadening our understanding of engineering student success beyond traditional academic competencies that are measured on the transcript. Findings from our research are meant to complement the ways in which engineering education researchers have supported student success in prior efforts through a deeper understanding of students' abilities and experiences beyond the classroom. Thus, further exploring the impact of non-cognitive competencies on engineering student success has great potential to inform new and existing strategies to further improve the way engineering is learned, taught, and practiced.

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