Validation of the Student Attitudinal Success Inventory II for Engineering Students

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I. Introduction

As low student retention rates in engineering programs in the United States continue to threaten the effort to increase the engineering workforce, various approaches have been utilized to investigate the putative factors that may contribute to attrition of engineering students[1,2]. Traditionally, cognitive indicators of students' pre-college academic performance, such as high school grade point average (GPA) and standardized achievement test scores (e.g., SAT and ACT scores), have served as main criteria to determine acceptance to engineering programs because of their assumed predictive validity of academic success in college[3]. However, recent studies have demonstrated evidence on the strong predictive power of noncognitive attitudes over cognitive measures of students in retention and their future academic performance[2,4].

For example, Robbins et al. (2004)[5] conducted a meta-analysis using 109 studies to examine the relationship between nine psychological constructs (achievement motivation, academic goals, institutional commitment, perceived social support, social involvement, academic self-efficacy, general self-concept, academic-related skills, and contextual influences) and college performance (cumulative GPA and persistence). They found that academic goals, academic self-efficacy, and academic related skills were moderately related to persistence, and academic self-efficacy and achievement motivation were the best predictors of cumulative GPA over pre-college cognitive indicators, such as standardized achievement test scores and high school GPAs. This implies that solely depending on traditional cognitive measures may not be sufficient to predict college students' performance, so embracing noncognitive measures may increase the predictive power of students' persistence and future performance in college.

As students' noncognitive attributes have gained more attention in academic performance and retention studies in higher education, this study describes a validation procedure for the extended version of the Student Attitudinal Success Inventory (SASI) to assess engineering students' multifaceted non-cognitive attributes.

A. Cognitive vs. Noncognitive Attributes

In the literature, there has been confusion conceptualizing the definition of cognitive and noncognitive attributes in the prediction studies of students' performance[5]. On the one hand, Messick (1979)[6] considered a broad spectrum of noncognitive variables like personality attributes, including affects, attitudes, interests, and motivation, and considered cognitive variables as intellectual abilities, including subject knowledge and information processing skills. On the other hand, based on the social cognitive theories, various researchers treated a broad range of motivational constructs, such as self-regulation, self-efficacy, expectancy-value, affect, learning strategies, and metacognitive strategies, as cognitive variables[7].

In this study, we define noncognitive attributes as psychometric traits and skills that are relevant to function for academic and occupational achievement of engineering students for operational purposes, while acknowledging that the distinction between these two concepts is not a black-and-white separation as most noncogntive traits usually involve cognitive components[6]. Therefore, noncognitive attributes include a range of psychometric attributes, such as personality, perseverance, motivation, and attitudes that facilitate an individual's functioning in a school system[8]. Considered noncognitive attributes in this study are academic motivation, problem solving strategies, learning approaches, self-beliefs, decision making, and social interaction that appeared in the literature as significant predictors of students' persistence, retention, and success in a school system.

B. Student Attitudinal Success Inventory (SASI)

In 2004, a group of researchers at a Midwestern university compiled a battery of psychometric instruments (later named as the Student Attitudinal Success Inventory [SASI]) to explore profiles of first year engineering (FYE) students' noncognitive attributes before their college entrance[9]. The SASI consists of 161 items that originated from existing instruments and were developed by the group of researchers based on theoretical frameworks from the literature. The nine constructs measured by the SASI are intrinsic motivation, academic self-efficacy, expectancy-value, deep learning approach, surface learning approach, problem solving approach, leadership, teamwork skill, and major indecision, each using a five-point Likert scale (strongly disagree, disagree, neutral, agree, and strongly agree).

Table 1 shows characteristics of the SASI, in terms of origins of items, the number of items, and sub-factors of each construct if any. Several studies supported the solid evidence of reliability and validity of the SASI[9,10]. For example, Reid (2009)[10] provided validity and reliability evidence of each construct measured by the SASI using multiple factor analyses and internal consistency reliability analyses. As some items were modified from the original items, psychometric properties of the modified measures might differ from the original scale. For example, the original State of Metacognitive inventory was designed to be administered after completing a task to measure college students' awareness of their thinking process when they were involved in the task. However, for the SASI, the inventory was modified to be domain specific for engineering students, which is situated in a problem solving process in general. Thus, the construct measured by the modified items becomes to measure engineering students' general approach to solve problems. In addition, items to measure engineering students' academic self-efficacy were tailored to measure their confidence of learning engineering basic subjects and academic skills necessary to complete their engineering programs.

Table 1. Noncognitive constructs measured by the SASI

ID	Construct	Origin	N_s	N_t	Subconstruct	N_i
1	Intrinsic Motivation	Academic Intrinsic Motivation Scale (AIMS) (French & Oakes, 2003)[11]	4	25	Career	5
					Challenge	6
					Control	7
					Curiosity	7
2	Academic Self-efficacy	Developed based on Bandura (1986)[12]	1	10	Academic Self-efficacy	10
3	Expectancy-Value	Developed based on Wigfield & Eccles (2000)[13]	5	32	Expected Use of Academic resources	5
					Community Involvement	4
					Employment Opportunities	8
					Persistence	7
					Social Engagement	8
4	Deep Learning Approach	Revised two-factor Study Process Questionnaire (R-SPQ-2F) by Biggs, Kember, & Leung (2001)[14]	2	10	Motive	5
					Strategy	5
5	Surface Learning Approach		2	10	Memorization	3
					Studying	7
6	Problem Solving Approach	Modified from the State Metacognitive Inventory by O'Neil & Abedi, (1996)[15]	4	20	Awareness	5
					Cognitive Strategy	5
					Planning	5
					Self-checking	5
7	Leadership	Developed based on Hayden & Holloway (1985)[16]	4	23	Motivation	5
					Planning	4
					Self-assessment	7
					Teammates	7
8	Team vs. Individual Orientation	Developed based on McMaster (1996)[17]	2	10	Individual Dynamic	5
					Team Dynamic	5
9	Major Indecision	Developed based on Osipow (1999)[18]	5	21	Certainty of Decision	3
					Difficulty in Decision	10
					Personal Issues	4
					Urgency	3
					Independence	1
	Total	9 instruments	29	161		161

Note. N_s = Number of subconstucts; N_t = number of the total items in the construct; N_i = number of the total items in the subconstruct.

After its first application in 2004 for FYE students[9], the SASI has been administered to more than 1500 FYE students each year for various research purposes at the university[9,19,20]. Since then, the SASI has been used in various empirical studies to explore profiles of FYE students in different conditions. For example, Immekus et al. (2005)[9] attempted to examine noncognitive profiles of students in the four different academic statuses after their FYE program: (a) successful and stayed at the university, (b) successful and left the university, (c) unsuccessful and stayed at the university, and (d) unsuccessful and left the university. Particularly, the SASI revealed differences in noncognitive characteristics between students who persist in engineering and who do not, and who are academically successful and who are not. Multiple studies have developed different models for student retention and success in engineering based on data collected with the SASI[21, 28, 29,30,31]. In those studies, the SASI has been utilized as an important measure to model student retention and matriculation in the engineering program[21, 22, 28, 31].

However, with increasing research evidence on other constructs relevant to students' college performance and retention, the SASI was extended to add 85 more items including the constructs of goal orientation, implicit beliefs, intent to persist, social climate, self-worth, and career decision. This resulted in a total of 246 items. Table 2 shows the characteristics of constructs added to the original version of the SASI. Therefore, validation of the extended version of the SASI (SASI II hereafter) becomes a necessary procedure because any modification and addition of items are likely to change the psychometric properties of the original instrument.

Table 2. Additional constructs included in the SASI II

ID	Construct	Origin	N_f	N_t	Subconstruct	N_i
10	Goal Orientation	Modified from PALS (Midgley et al., 2000)	7	33	Mastery goal orientation (GO)	5
					Performance-approach GO	5
					Performance-avoid GO	4
					Classroom mastery goal structure (GS)	6
					Classroom performance-approach GS	3
					Classroom performance-avoid GS	5
					Avoiding Novelty	5
11	Implicit Beliefs	Dweck, Chiu, & Hong (1995)	2	6	Implicit Theory on Intelligence	3
					Person as a whole(Type of person)	3
12	Intent to Persist	Cabrera et al. (1993), Pascarella & Terenzini (1980)	3	15	Institutional goal commitment	6
		Noel-Levitz (1988)			Desire to finish college	4
		Developed			Desire to major in engineering	5
13	Social Climate	Cabrera et al. (1993)	2	9	Environmental	4
		PALS (Midgley et al., 2000)			Neighborhood space	5
14	Self-worth	Crocker et al. (2003)	3	15	Other's approval	5
					Competition	5
					Academic competence	5
15	Career Decision	Developed based on Osipow (1999)[18]	2	7	Personal Issues	4
					Urgency	3

Note. N_s = number of subconstucts; N_t = number of the total items in the construct; N_i = number of the total items in the subconstruct; PALS denotes Patterns of Adaptive Learning Questionnaire (PALS)

C. Purpose of the Study

The main purpose of developing the SASI II is to assess engineering students' noncognitive attributes and to use the collected data to predict students' performance in engineering and persistence in the program. This paper examines two questions regarding the SASI II. First, as the SASI II contains many constructs and items, this study aims to investigate the SASI II as a whole and keep only essential constructs and items through psychometric evaluation, providing reliability and construct validity evidence of the SASI II. Second, as the SASI II was designed to assess engineering students' profile of noncognitive attributes, which might be critical to be successful in their engineering programs, it is necessary to investigate the association between engineering students' noncognitive profile, measured by the SASI II and their performance in engineering. Therefore, the main goal of this study is to rigorously validate the SASI II, as a tool for assessing engineering students' multifaceted noncognitive attributes that relate to their college academic performance. Following research questions guided this study.

1. To what extent does construct validity of the SASI II hold?
2. What level of internal consistency reliability exists for FYE students' data from the SASI II?

II. Methods

A. Sample and Procedure

The SASI II was constructed on line using a web-based survey program. Since the SASI II consists of 246 items, which is very long for students to respond it all at once, it was evenly split into three parts, so students were able to access each part of the survey whenever they were available before their entrance of the program. The target population for the use of SASI II was FYE students at a Midwestern university.

In 2007, more than 1,700 students, who enrolled to attend a FYE program at Purdue University, were invited to respond to online surveys during the summer before their start of the program. Among them, 1,182 students (N_M = 943 [79.8%], N_F = 239 [20.2%]) completed the SASI II. In 2008, similarly, more than 1,700 students were invited to respond on the same survey. Among them, 1,695 students (N_M = 1,309 [77.2%], N_F = 380 [22.4%]) completed the SASI II. Demographic information was retrieved from the university archive. Table 3 shows demographic characteristics of those students who entered the FYE program at the university in 2007 and 2008 respectively.

Table 3. Characteristics of the FYE students who responded on the SASI II

Category	2007		2008	
	*N**	%	*N**	%
Gender				
Female	239	20.2	380	22.4
Male	943	79.8	1,309	77.2
Unspecified	0	0.0	6	0.4
Domestic	991	83.8	1,500	88.5
International[a]	191	16.2	195	11.5
Race/Ethnicity[b]				
Hispanic	39	3.3	33	1.9
American Indian or Alaska Native	8	0.7	6	0.4
Asian	15	1.3	97	5.7
Black	28	2.4	31	1.8
Native Hawaiian or other Pacific Islander	0	0.0	0	0.0
White	807	68.3	1,315	77.6
Multi-racial	0	0.0	3	0.2
Unspecified	94	8.0	15	0.9
Total	1,182	100.0	1,695	100.0

Note. *Due to unspecified responses, the numbers are inconsistent with the total number of participants; [a]International students' race/ethnicity information was not categorized; [b]Race/Ethnicity category includes only domestic students.

B. Data Analyses

To answer each research question, we considered the following data analyses methods: factor analyses for construct validity and internal consistency reliability analyses for reliability. The five-point Likert scale used in the SASI II is naturally categorical and the distribution of responses for each item was skewed and did not follow a normal distribution. Therefore, robust weighted least squares (WLSMV) employed in Mplus 7.11[23] was utilized as an estimator to obtain parameter estimates for factor analyses with categorical data.

First, an exploratory factor analysis (EFA) was conducted using the 2007 cohort data to identify underlying factor structure and irrelevant items that did not fit into any factors that exist in the inventory. For the EFA, eigenvalues, and factor loadings after oblique rotation of GEOMIN, which is the default rotation of the M*plus*, were calculated to judge the number of factors and items for each factor. Second, after identifying the factor structure and relevant items for the SASI II, we conducted confirmatory factor analyses (CFAs) using the 2008 cohort data to confirm and refine the factor structure of the SASI II identified through the EFA. Based on the fit indexes that M*plus* provides, the Chi-square, root mean square error of approximation (RMSEA), comparative fit index (CFI), and Tucker-Lewis index (TLI) were used to judge CFA model fits[24]. We attempted various factor structure models with the items identified as the result of the EFA to refine the model fits of the CFAs using a structural equation modeling (SEM) approach. Finally, as we finalized a factor structure and items for the SASI II, we calculated the reliability coefficient of internal consistency, Cronbach's α, using SPSS Statistics 22 (IBM Corp., 2012), to investigate how items are inter-related within each factor, sub-factor, and the overall instrument.

III. Results

A. Construct Validity Evidence

Exploratory Factor Analysis Modeling. Polychoric correlation coefficients among the 246 items, which are ordered categorical variables, revealed that the coefficients were positively or negatively correlated, meaning that putative factors identified through an EFA are not independent. In addition, multicollinearity (strong correlations over .85) existed between several items, implying that those items might measure the same aspect of the constructs. Therefore, deletion of redundant items was considered after examination on the content. We extracted the number of factors underlying the data based on the point of inflection of the curve in the scree plot[26]. This yielded sixteen factors considered for inclusion in a putative factor structure for the SASI II. According to Stevens' (2002)[27] guideline about the relationship between the sample size and cutoff factor loading, we considered items with a factor loading greater than 0.40 significant for the designated factor. This cutoff functioned to suppress any irrelevant items that did not fit well into the designated factor. In addition, if an item loaded onto more than one factor, then the item was excluded. This resulted in no items loaded onto the last factor with a value greater than the cutoff value of factor loading. Thus, the last factor was not included in the final factor structure of the SASI II in CFAs. This resulted in 162 items, out of the original 246, that had significant factor loadings onto one of fifteen factors, indicating each item's unique contribution to one of the factors.

Based on the original instruments of the items and theories applied to develop items, we matched the constructs to the factors clustered with a group of items. The fifteen factors were named as (a) academic motivation (MTV), (b) persistence (PST), (c) mastery learning goal orientation (MLG), (d) personal achievement goal orientation (PAG), (e) deep learning approach (DLA), (f) surface learning approach (SLA), (g) problem solving approach (PSA), (h) implicit beliefs about intelligence and person as whole (IMB), (i) self-worth in competition (SWC), (j) self-worth in other's approval (SWO), (k) social engagement (SCE), (l) teamwork (TWK), (m) decision making in college major (DMC), (n) fit with major/career (FIT), and (o) occupational confidence (OCC).

Confirmatory Factor Analysis Modeling. Several CFAs were conducted to confirm and refine the factor structure for the SASI II using 2008 cohort data. We evaluated each CFA model with three steps: (a) checking the consistency of multiple goodness-of-fit indexes and judging the fit of the obtained CFA model to the data; (b) examining localized areas of poor fit, if any; and (c) inspecting parameter estimates, such as factor loadings, factor variances, and residual variances to ensure the observed data's reliability on each item to the latent factor[24]. The first model with fifteen factors, which resulted from the EFA, yielded a poor fit. As a CFA requires more constraints in the relationships between items and factors than the model identified though an EFA[24], we modified the initial factor model by removal of items that behaved poorly based on the modification index provided by M*plus*[24].

Accordingly, CFA model respecification was done in several ways based on the factor correlations and the modification indices (i.e., specific areas of the model misfit that show items with a discrepancy between the data and the proposed model). First, we conducted a CFA for each construct independently and refined the factor structure of each construct. During the process, redundant items, items with poor factor loadings, and items that cause large modification indices were eliminated to acquire a parsimonious solution. Second, based on the theory and validation studies using the instruments, which are the origin of the items used in the SASI II, we applied a sub-factor structure of some constructs, using structural equation modeling approach. This approach resulted in the improved fit indexes in the CFA model of some constructs as well as construct validation of each construct independently. Third, after refining the factor structure of each construct, we tested the overall CFA models with the fifteen constructs. Again, problematic items, such as items with poor factor loadings and items that cause large modification indices, were eliminated.

Finally, we arrived at the final model with fifteen constructs indicated by 130 items. All factor loadings were significant and all fit indexes were in a good-fit range ($\chi^2(8151) = 25451.33$, $p < 0.01$, $RMSEA = 0.035$, $CFI = 0.932$, $TLI = 0.930$). Factor correlation coefficients among the fifteen factors ranged from -0.61 to 0.95. Depending on the types of learning approach – adaptive (deep learning approach) vs. maladaptive (surface learning approach), or learning goals – mastery learning goal vs. personal achievement goal, the correlation coefficients among the constructs varied from positive to negative relationships.

B. Reliability Evidence

Data from the FYE students in the 2008 cohort were utilized for the reliability analysis. The overall reliability of the SASI II with 130 items was Cronbach's α = 0.931 (N = 1,695). Each construct housed in the SASI II appeared to have good internal consistency as shown in Table 4. Cronbach's α values of the 15 constructs ranged from 0.739 to 0.942 for 2008 data. Cronbach's α values of subconstructs were relatively lower than their upper constructs, but in an acceptable range, which are from 0.718 to 0.905. All items of the SASI II were worthy of inclusion because the removal of any items would not increase the score reliability for any sub-factor, factor, and the SASI II as a whole[25].

Table 4. Internal consistency reliability coefficients (Cronbach's α) of the constructs from the 2008 cohort SASI II data

Construct	Acronym	N_t	Cronbach's α	Subconstruct	Acronym	N_i	Cronbach's α
Academic motivation	MTV	24	0.942	Intrinsic motivation	MTVI	14	0.905
				Academic self-efficacy	MTVS	10	0.894
Persistence	PST	8	0.895	In engineering	PSTE	4	0.845
				In university	PSTU	4	0.840
Mastery learning goal orientation	MLG	6	0.878				
Personal achievement goal orientation	PAG	10	0.912	Performance approach	PAGA	5	0.877
				Performance avoid	PAGD	5	0.837
Deep learning approach	DLA	9	0.839				
Surface learning approach	SLA	13	0.860	Avoiding novelty	SLAA	5	0.794
				Memorization	SLAM	3	0.718
				Surface strategy	SLAS	5	0.746
Problem solving Approach	PSA	14	0.899				
Implicit beliefs about intelligence and person as whole	IMB	6	0.860				
Self-worth in competition	SWC	5	0.848				
Self-worth in other's approval	SWO	3	0.784				
Social engagement	SCE	5	0.788				
Teamwork	TWK	7	0.774				
Decision making in college major	DMC	10	0.924				
Fit with major/career	FIT	6	0.768				
Occupational confidence	OCC	4	0.739				

Note. N_t = number of the total items in the construct; N_i = number of the total items in the subconstruct.

IV. Summary and Conclusion

The purpose of the study was to validate the SASI II in order to provide an instrument to measure engineering students' multifaceted noncognitive attributes. As various items were originated from the existing instruments and/or modified specifically for the use of engineering students, an EFA was conducted to identify the underlying factor structure of the SASI II. Then, several CFAs were followed to refine and finalize the factor structure of the inventory.

As a result, a factor model using structural equation modeling showed good model fit indexes in which130 items were loaded onto one of the fifteen constructs. Based on the theoretical background of the items, the fifteen construct were named as academic motivation (MTV), persistence (PST), mastery learning goal orientation (MLG), personal achievement goal orientation (PAG), deep learning approach (DLA), surface learning approach (SLA), problem solving approach (PSA), implicit beliefs about intelligence and person as whole (IMB), self-worth in competition (SWC), self-worth in other's approval (SWO), social engagement (SCE), teamwork (TWK), decision making in college major (DMC), fit with major/career (FIT), and occupational confidence (OCC). As evidence of internal consistency reliability, Cronbach's α values of fifteen constructs were all in the acceptable range. Table 5 contains the definition for each construct and subconstruct if any exist. Significant factor correlation coefficients among the fifteen constructs indicate that they are not independent but positively or negatively correlated to some degree.

Table 5. Definition of the Constructs measured by the SASI II

Construct (Acronym)	Definition
Academic motivation (MTV)	Students' overall academic motivation that consists of two subconstructs: intrinsic motivation (MTVI) and academic self-efficacy (MTVS). Intrinsic motivation (MTVI) indicates students' beliefs about their overall confidence in challenging academic work, learning new materials, and working in their chosen profession. Academic self-efficacy (MTVS) refers students' beliefs in future performance to learn engineering basic subject knowledge (mathematics, chemistry, and physics) and academic skills (writing, communication, programming, problem solving, creative thinking, study skills, and teaming skills).
Persistence (PST)	Students' desire and commitment to finish their engineering program (persistence in engineering, PSTE) and achieve a college degree in the university (persistence in university, PSTU).
Mastery learning goal orientation (MLG)	Students' orientation to extend their knowledge and understanding for mastery learning with attention focused on the self.
Personal achievement goal orientation (PAG)	Students' orientation to demonstrate their personal achievement that consists of two subconstructs: performance approach goal orientation (PAGA) and performance avoid goal orientation (PAGD).Performance approach goal orientation (PAGA) refers students' purpose or goal to demonstrate their competence to others. Performance avoid goal orientation (PAGD) refers students' purpose or goal to avoid the demonstration of incompetence from others.
Deep learning Approach (DLA)	Students' learning approach to engage coursework appropriately.
Surface learning Approach (SLA)	Students' surface learning approach consists of thee subconstructs: avoiding novelty (SLAA), memorization (SLAM), and surface strategy (SLAS). Avoiding novelty (SLAA) indicates students' learning approach to avoid unfamiliar or new work. Memorization (SLAM) refers students' preference of learning by rote memorization. Surface strategy (SLAS) indicates students' learning approach with minimal effort to pass the course.
Problem solving Approach (PSA)	Students' perception of their approach to solve problems in terms of their awareness in the problem solving process and strategies.
Implicit beliefs (IMB)	Students' beliefs about intelligence and person as a whole that are a fixed and nonmalleable entity so that remain the same.
Self-worth in Competition (SWC)	Students' self-esteem based on being superior to others in competition.
Self-worth in other's approval (SWO)	Student's self-esteem based on other's approval and acceptance.
Social engagement (SCE)	Students' expectation about social engagement with different people in college.
Teamwork (TWK)	Students' perception of team dynamics to work as a team in terms of responsibility, respect, and communication.
Decision making in college major (DMC)	Students' perception of difficulty in making a decision regarding a college major due to various reasons.
Fit with major/career (FIT)	Students' belief about their match with a major and a career.
Occupational confidence (OCC)	Students' confidence to locate occupational information to prepare a future career.

As the SASI II was designed to measure engineering students' noncognitive attributes, the following aspects make the SASI II significant for the use in the engineering education research. First, the constructs and items were specifically designed for engineering students. For example, the SASI II addresses aspects of academic self-efficacy in engineering basic subjects and academic skills to be successful in the engineering program, problem solving approach, working as a team, and persistence to stay with the institution/university and engineering program. Therefore, by exploring engineering students' responses on the SASI II, researchers and educators will be able to investigate the dynamics of noncognitive attributes that may relate to students' performance and success in their program at various points (e.g. before and after freshman or sophomore years). Second, the results of this effort can be used to predict engineering students' success, as well as identify students at risk of academic failure. Thus, program advisors or counselors will be more informed about the students and able to provide proactive guidance or advising for students at risk.

As this study initiated the first step to validate the SASI II, additional validity evaluations, such as convergent, discriminant, concurrent, and predictive, are recommended for the following steps for a future study. In addition, item analyses based on classical test theory and item response theory will reveal psychometric properties of the SASI II at the individual item level as well as the whole test. As students' noncognitive attributes have gained more attention in academic performance and retention studies in higher education, we expect that the SASI II can be used as a sound and all-around instrument to measure engineering students' noncognitive attributes for various research and education purposes.

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