AC 2008-1995: NONCOGNITIVE CHARACTERISTICS OF INCOMING ENGINEERING STUDENTS COMPARED TO INCOMING ENGINEERING TECHNOLOGY STUDENTS: A PRELIMINARY EXAMINATION

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Noncognitive Characteristics of Incoming Engineering Students Compared to Incoming Engineering Technology Students: A Preliminary Examination

Abstract: Studies have shown promise in predicting success for students in engineering based on noncognitive or affective characteristics. However, little if any literature exists on similar studies in the related discipline of engineering technology.

Data has been collected from incoming engineering students in a large, Midwestern university using an instrument assessing students' self-reported noncognitive characteristics over a four year period. The instrument has been shown to be stable and repeatable over this four year period. Cluster analysis has shown that students entering engineering cluster into three distinct groups. Five additional constructs have been added to the survey for the current cohort of students.

This paper will examine results of an analysis of students in a pilot study in engineering technology using the same instrument already in use for incoming engineering students. Differences found between engineering and technology cohorts will be presented to the extent that the relatively small sample of technology students will allow. Finally, suggestions for future work in this area, the suggested applicability of individual items in the instrument and potential findings within the data will be presented.

An effective instrument will allow for the development of a model to predict success, currently operationalized as retention into the second year. Such a model should prove to be valuable to address long standing issues of gender and ethnic disparities within engineering technology and should lead to improved advising and improved overall student success.

Introduction:

Engineering and engineering technology are comparatively lucrative fields of employment with continued strong demand. These fields attract academically strong students; however, graduation rates in engineering programs have been shown to be at or around 50% nationwide. Astin[1] showed that only 44% of students entering engineering showed engineering as their major four years later. The National Academies report "Rising Above the Gathering Storm"[2] describes technical programs as having some of the lowest retention rates among academic disciplines. Studies have shown that students who leave engineering tend to show differences in their noncognitive characteristics rather than cognitive ability or academic performance[3,4].

An instrument consisting of 161 items designed to assess noncognitive characteristics of incoming students was originally designed to assess characteristics of incoming engineering students. The instrument was used to assess nine noncognitive constructs, specifically focusing on those characteristics for which an institution may be able to develop intervention strategies / programs rather than an attempt to simply collect a wide range of data. Data has been collected for a four year period for incoming engineering students and were found to be psychometrically stable and robust[5]. Additional characteristics which showed promise as being predictive of retention were found in a further review of the literature. Five additional constructs were added to the survey for students in the 2007 cohort for a total of fifteen constructs measured in 239 items.

The overall intent is to find characteristics which may predict a student's propensity to remain in an engineering program into the second year then incorporate this information in the development of a predictive model. It is theorized that a complete model to predict student matriculation into the second year should incorporate noncognitive characteristics in addition to cognitive variables as inputs; data that can be collected prior to the beginning of the first-year is expected to be especially useful as it would allow for more effective structuring of a student's first-year experience.

Similar instruments

The Cooperative Institutional Research Program (CIRP) Freshman Survey covers a wide variety of attributes. These include attributes of the student's background (for example, financial state of the family), self reported noncognitive attributes from the student (attitudes towards school) and cognitive information (high school performance). This large database holds information for over 190,000 students at over 300 institutions. High school GPA, SAT math scores and SAT verbal scores were shown to be cognitive predictors of future performance (defined as collegiate GPA). Self-ratings of ability in mathematics, computers and overall academic ability were shown to be noncognitive predictors[6,7].

The Pittsburgh Freshman Engineering Attitudes Survey (PFEAS) measures 13 characteristics using self-reported answers to 50 items. Students who left engineering were found to have a significant difference in "general impression of engineering", "perception of the work engineers do for the engineering profession" and "engineering comparing positively to other fields of study". Students who left also had a lower self-reported confidence in their engineering skills[8].

Zheng[9] reported on the relation between retention and six cognitive and noncognitive variables in a study using the Southeastern University and College Coalition for Engineering Education (SUCCEED) longitudinal database. Correlation between high school GPA and SAT math scores and retention was shown, although results varied by campus. Reasons cited for students leaving engineering included an inability to handle stress, a mismatch between personal expectations and college reality and lack of personal commitment to a college education.

The Persistence in Engineering (PIE) instrument was developed as part of the overall Academic Pathway Study (APS)[10]. This survey covers a wide variety of characteristics from environmental (financial), post enrollment (attitudes about the first year experience) and self reported noncognitive characteristics (motivation). Noncognitive predictors of retention into the fourth year of engineering included motivation due to family member influences, confidence in math and science and level of engagement in the classroom[11].

These instruments collect data during the first year of study and/or data which, while potentially predictive, isn't always likely to be affected by first year programs or intervention strategies.

Seymour and Hewitt report that students who left and students who remain in engineering were very similar in their academic abilities[12]. Students who left primarily cited reasons dealing with the culture of the institution and aspects of engineering as a career rather than academic factors.

Taken as a whole, the literature suggests that differences in noncognitive characteristics may play a more important role in retention in engineering than differences in cognitive characteristics. This would suggest that interventions assisting in noncognitive needs of students prior to and during the first year of study would benefit more students than strictly academic assistance. As stated by Pascarella,[13] "A significant amount of student attrition may be prevented through timely and carefully planned institutional interventions. Such interventions will be most effective if those students with a high probability of dropping out can be accurately identified."

Constructs in the instrument:

The initial instrument consisted of nine constructs divided into subconstructs as specified in their original design or discovered though factor analysis.

Motivation: Motivation was evaluated using the Academic Intrinsic Motivation Scale (AIMS)[14], a scale consisting of 25 items with four subfactors: *Control*, *Challenge*, *Curiosity* and *Career*.

Metacognition: The Metacognition scale consists of *planning*, *self-monitoring*, *cognitive strategy* and *awareness* subfactors. This describes a student's perception of their strategies for monitoring and modifying their cognition[15,16].

Deep learning and *Surface learning*: Items for these scales were adapted from the Study Process Questionnaire (SPQ)[17]. Deep Learning consists of subfactors *motive* (or intrinsic interest) and *strategy* (or maximizing meaning). The surface learning construct consists of *memorization* and *studying*.

Self-efficacy: Many studies indicate the importance of self-efficacy and it has been shown to be predictive of retention[18,19]. No subfactors were found in this ten-item scale.

Expectancy-Value: The expectation of the value placed in each of four subfactors, including *employment opportunities*, *persistence*, *academic resources* and *community involvement* is assessed in these 32 items.

Major Indecision: The scale items in Major Indecision were developed based on models of career indecision as described by Osipow[20], who discusses a number of different career indecision inventories. The Major Indecision scale consists of 21 items with the following subfactors: *urgency*, *personal issues* (related to the student's choice in major), *certainty of decision* and *difficulty in decision* (self-assessment of the student's tendency to be indecisive in general). One item was unaccounted for in these subfactors and is treated separately (*independence).*

Leadership: The student's self assessment of their leadership is based on four subfactors including *self-assessment* (primarily self assessment of their organizational and leadership skills), *motivation*, *planning* and (interaction with) *teammates*. Characteristics of leadership are theorized to have a positive effect on student retention[21].

Team vs. Individual Orientation: A student's ability to contribute to a team environment is increasingly valuable in industry. This construct is comprised of two subfactors: *individual* and *team dynamic* and consists of 10 items.

A bifactor model structure was found, allowing each item to load to a construct and exactly one subfactor within that construct. This model structure implies that each subfactor is orthogonal or independent of other subfactors.

Internal consistency, a common measure of reliability, was assessed within each construct and subfactor. In each case, the value of Cronbach's coefficient alpha exceeded 0.75, demonstrating the homogeneous nature of the scales by exceeding recommended minimum values of 0.75 [22]. Little to no variation in the values of alpha were seen when comparing constructs and subfactors from 2004 through 2006, one indication of the stability of the data. Confirmatory Factor Analysis (CFA) was used to assess the fit of the model based on aggregate 2004-2006 data (engineering students, N=5416). Statistics showing a valid model structure included the Goodness of Fit Index (GFI), the Comparitive Fit Index (CFI) and Root Mean Square Error of Approximation (RMSEA)[23, 24].

Five additional constructs were included with the instrument for the 2007 cohort of students. These constructs were:

Goal Orientation: Seven subfactors within the Goal Orientation construct as defined in The Patterns of Adaptive Learning Questionnaire (PALS)[25] were investigated. Confirmatory factor analysis supported the model structure in their application. Subfactors include *Mastery Goal Orientation, Performance-Approach Goal Orientation, Performance Avoidance Goal Orientation, Classroom Mastery Goal Structure, Classroom Performance Approach Goal Structure, Classroom Performance Avoidance Goal Structure* and *Avoiding*. The total number of additional items is 33 for this construct.

Implicit Beliefs: Dweck[26] presents data showing that a student's implicit beliefs about their ability can act as a predictor of whether the student will be oriented toward developing their ability (learning) or toward documenting the adequacy of their ability (performance). Two subconstructs were included: *Implicit Theory on Intelligence* and *Person as a Whole*, for an additional 6 items.

Intent to Persist: Seven new items assessing a student's intent to persist[27,28] are based on original items from the work of Tinto and Bean[29,30]. In total, 15 additional items are included in the instrument.

Social Climate: Studies have indicated a positive correlation between student involvement or integration into their college experience and likelihood to persist[31,32,33]. Among students who persist, higher gains in learning are shown in students who report higher levels of contact with their peers. Nine additional items based on those from the PALS and Cabrera's work[34].

Self-Worth: Items forming the construct Self-Worth originate from scales originally presented by Crocker[35]. A study showed a correlation between self esteem / self worth and student grades. Self esteem and self-efficacy of female students in engineering were found to be particularly affected by receiving grades below their expectations in theory exacerbated by the culture of engineering. Fifteen new items were included with three subfactors.

Analysis of internal consistency and model structure with the complete 14 construct instrument was completed using the 2007 cohort of students. Values for all constructs previously reported were consistent with the 2004-2006 cohorts. Values of alpha for each construct were found to exceed 0.75.

Method and participants

Data from students early in their first year of study in Engineering Technology were collected along with data from incoming engineering students for the fall 2007 semester. Students entering engineering are required to take this assessment as part of the admissions process through Freshman Engineering, so all incoming engineering students are represented in the data. The instrument is broken into three separate Internet pages; students who did not complete each page were excluded.

Students entering engineering technology in the specific programs in this study do not pass though required testing within engineering technology or common advising programs prior to scheduling their first semester courses, but instead are advised by individual departments or units within technology. Since there was no mechanism to require students to take the assessment, individual courses required in the first semester of study in different technology programs were identified, and the instructor in each course was asked to assign the survey as a homework assignment. This led to some inconsistency from program to program.

Overall, data from technology students were collected within the first three weeks of their first semester from a number of courses from introductory courses in participating institutions including Purdue University, Indiana University Purdue University Indianapolis (IUPUI) and Texas A&M University (TAMU). The number of participants is shown in Table 1:

Table 1: Participants by Discipline and Location

Discipline	Course	Number of Students
Engineering (Purdue)	Freshman Engineering	1182
Technology		159
Mech Engr Tech (Purdue)	MET 104	4
Comp Info Tech (IUPUI)	CIT 106	45
Comp Graphics Tech (IUPUI)	CGT 110	25
Elec & Comp Engr Tech (IUPUI)	ECET 109	25

Construction Tech (IUPUI)	CNT 105	17
Architectural Tech (IUPUI)	ART 299	17
Biomedical Engr Tech (IUPUI)	BMET 105	4
Mech Engr Tech (IUPUI)	MET 105	5
Elec & Comp Engr Tech (TAMU)	ECET	17

Some IUPUI students were enrolled in multiple courses in the list; in these cases, they were restricted to participating only once by the system.

Results

Initial results of a comparison between the two populations primarily involved examination of statistically significant differences in the means of each construct. Subfactors and individual items were also examined.

Significant differences are determined by use of the Wilcoxon-Mann-Whitney test with a very conservative value of p=0.001. This data is Likkert scale (therefore ordinal), and does not meet a normal distribution, thus the Wilcoxon-Mann-Whitney test is appropriate. A conservative value of p was selected to guard against Type I error, allowing almost no chance that the null hypothesis should be erroneously accepted; in other words, false findings of statistically significant differences should be nearly impossible.

Analysis and discussion will be broken into highly statistically significant, slightly statistically significant and not statistically significant for this initial analysis.

Those constructs with a high statistical difference are shown in Table 2:

Table 2: Constructs with a High Statistical Significance

Construct	Mean, engr	Mean, tech	H	P
Social Climate	4.17/5.00	3.75/5.00	92.4	<0.0001
Expectancy-Value	3.95	3.64	82.1	<0.0001
Teamwork	3.94	3.67	46.3	<0.0001
Intent to Persist	4.20	3.88	45.6	<0.0001
Self-efficacy	4.22	3.91	41.6	<0.0001
Motivation	4.0	3.89	24.6	<0.0001

Slight, but statically significant differences are shown in Table 3:

Table 3: Constructs with a Slight Statistical Significance

Construct	Mean, engr	Mean, tech	H	P
Surface Learning	2.44/5.00	2.63/5.00	19.3	<0.0001
Leadership	3.93	3.76	17.0	<0.0001
Deep Learning	3.70	3.53	16.1	<0.0001
Metacognition	3.94	3.79	15.4	<0.0001

Finally, those constructs with little to no statistical difference are shown in Table 4:

Table 4: Constructs, Little to no Statistically Significant Difference

Construct	Mean, engr	Mean, tech	H	P
Major Indecision	3.51	3.43	4.2	0.040
Goal Orientation	3.45	3.39	3.2	0.074
Self-Worth	3.29	3.27	1.2	0.270
Implicit Beliefs	2.64	2.68	0.8	0.370

Discussion of Results

The greatest differences between the students entering these disciplines appear to be in those characteristics that would separate the climate of engineering and technology. The two primary characteristics are Social Climate and Expectancy-Value. Subfactors of Expectancy-Value including “Social Engagement”, “Use of Academic Resources”, and “Community Involvement” also relate to the Social Climate construct. The Teamwork construct appears to relate to some subfactors including “Community Involvement” and “Social Engagement” as well as “Intent to Persist, Individual” which relates to an individual’s teamwork orientation.

The Intent to Persist construct is also significantly different; many subfactors in this construct are similar to those in Self-Efficacy and Motivation which also show significant differences.

Further analysis validating the constructs must be done before definitive conclusions can be reached, and further analysis as to the predictive nature of these constructs must be complete before a judgment as to their importance in retention can be formulated. However, clear similarities do seem to emerge when examining the items at the subfactor level, and show that students appear to perceive their social climate and the value they expect from their major different between these disciplines. Students also show differences in their motivation and self-efficacy, which could relate to typical cognitive measures of incoming students (high school GPA, standardized test scores, etc.)

Those characteristics with slight differences include constructs related to the (self reported) learning style and academic ability of the student (with the exception of self-efficacy). Engineering students show a propensity more towards deep learning and away from surface learning and a slightly higher self-reported metacognitive ability. One of the subfactors of Goal Orientation, “Classroom Mastery Goal Structure” shows a similar slightly higher value or engineering students and seems related to these constructs.

Leadership, found to be slightly different, showed some subfactors (“planning” and “motivation”) to be comparable to Teamwork; other subfactors (“teammates” and “self-assessment”) were found to have little to no difference. It appears that assessment of a student’s individual abilities within a team appear nearly the same between engineering and technology students.

Implicit Beliefs and Self-Worth appear to have little if any difference between students in engineering and technology. Except for the difference in Self-Efficacy, students generally appear to view their value of themselves and their individual intelligence about the same regardless of their discipline.

Conclusions and ongoing efforts

While there are a number of first year surveys assessing noncognitive characteristics of incoming students, the instrument under development is unique in that it focuses exclusively on those characteristics for which intervention strategies may be implemented in the first year of study. The development of an instrument which is demonstrated to give valid, reliable and repeatable data on students prior to the beginning of their first year will be of benefit to both the student and the institution. Clearly, implementing this instrument for both engineering and engineering technology will require a method for participation of all incoming engineering technology students.

The data will be analyzed further to assess statistically significant differences in student responses based on gender, ethnicity and intended major. Further work to validate the constructs through qualitative means is also ongoing.

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