Is Modeling of Freshman Engineering Success Different from Modeling of Non-Engineering Success?

Cindy P. Veenstra
Department of Industrial and Operations Engineering
University of Michigan

Eric L. Dey
School of Education
University of Michigan

Gary D. Herrin
Department of Industrial and Operations Engineering
University of Michigan

Abstract

The engineering community has recognized the need for a higher retention rate in freshman engineering. If we are to increase the freshman retention rate, we need to better understand the characteristics of academic success for engineering students. One approach is to compare academic performance of engineering students to that of non-engineering students. This study explores the differences in predicting academic success (defined as the first year GPA) for freshman engineering students compared to three non-engineering student sectors (Pre-Med, STEM, and non-STEM disciplines) within a university. Academic success is predicted with pre-college variables from the UCLA/CIRP survey using factor analysis and regression analysis. Except for the factor related to the high school GPA and rank, the predictors for each student sector were discipline specific. Predictors unique to the engineering sector included the factors related to quantitative skills (ACT Math and Science test scores and placement test scores) and confidence in quantitative skills.

Keywords: CIRP survey, freshman engineering success, pre-college characteristics

I. Introduction

With the publication of *The Engineer of 2020,* the engineering education community has focused on the need to improve engineering student retention (Clough, 2004). NSF statistics show that the percent of all bachelor degrees earned in engineering has decreased from 7 percent to 5 percent over the past 20 years (National Science Foundation (NSF), 2006). Engineering education leaders have indicated a need for more engineering students and a higher retention of engineering students. Several sources state that less than half of the students who start in engineering as freshmen persist to graduate in engineering (Besterfield-Sacre, Atman, and Shuman, 1997; NSF, 2004; National Academy of Sciences (NAS), 2005). Several retention studies have shown that the Grade Point Average (GPA) contributes to the student's decision to persist in engineering college (French, Immekus, and Oakes, 2005; Burtner, 2004; Zhang et al., 2006). In particular, Zhang et al. reviewed the relationship between the college GPA and retention at nine engineering colleges, covering a fifteen-year period. They found that, within three semesters, most students with low GPAs had switched out of engineering. Zhang et al. also reported that a very low percentage of engineering graduates earned a first year GPA of less than 2.0. This research points to the need to understand the predictors of freshman academic success.

This study was undertaken to show the predictors of freshman academic success (defined here as the first year GPA) for engineering students compared to non-engineering students at the University of Michigan. Central to this research effort is whether the predictors of student academic success will be equivalent for engineering and non-engineering students. The University of Michigan has a common admissions process for all students, and engineering students take the same math and science courses as non-engineering students. Because the University of Michigan has a very selective admissions process, there was research interest in whether the same pre-college characteristics would be predictors of academic success for both engineering and non-engineering students. Due to the interest in pre-college characteristics and the availability of its data, the UCLA/Cooperative Institutional Research Program (CIRP) survey was used as the survey instrument. The CIRP survey is conducted during freshman orientation each year.

A summary of research studies related to engineering academic success is presented in Table 1. In all the studies of college GPA we reviewed, the high school GPA or rank was consistently a significant predictor of academic success. The Astin and Astin (1992) study showed that a number of CIRP variables were important for retention as an engineering major, including the SAT Math and self-rating of math ability. In addition, the Nicholls et al. (2007) study showed that most of the same CIRP variables were identifiers of STEM majors. The variables that were previously found to be significant predictors of academic success were considered for inclusion in this study.

Similar to the French, Immekus, and Oakes (2005) study, two cohorts were used in this study; the 2004 cohort was used to develop the prediction equation for first year GPA and the 2005 cohort was used to cross-validate the prediction. Most of the studies in Table 1 showed

Study/ Reference	Survey	Description	Key Predictors
Levin and Wyckoff 1988	N/A	Freshman engineering study at Penn State	Predictors for first year GPA include: High School GPA, SAT Math, math and chemistry placement test scores, gender and anticipated study time. $R^2 = 0.21$
Astin and Astin 1992	CIRP	Multi-institutional study of 388 universities; looked at engineering majors	For engineering retention: SAT Math, self-rating in math, aspiring to a career in engineering, high school GPA, strong orientation towards science.
Seymour and Hewitt 1997	CIRP/ Study	Includes STEM students from seven universities	Some STEM students indicated that their high school had not adequately prepared them. Engineering majors tend to be more committed to their career choice.
Besterfield-Sacre, Atman, and Shuman, 1997	PFEAS	First term GPA study, University of Pittsburgh	Predictors for first term GPA were: whether student had a scholarship, high school rank, SAT Math, self-assessment of study habits, self-rating of liking math and science and financial influences for an engineering major. $R^2 = 0.29$
Shuman et al. 2003	CIRP	Model whether a student would be placed on academic probation	Frequency in high school of coming to class late, self-rating of academic ability
Lotkowski, Robbins, and Noeth, 2004	N/A	Meta-analysis of 109 College retention studies	For college success (4-year), study found that the high school GPA, ACT assessment and academic self-confidence were strong predictors.
French, Immekus, and Oakes. 2005	N/A	Three-year study. Two cohorts; one to predict college GPA; the second to cross-validate	Predictors for college GPA were SAT Math, high school rank and a measure of academic motivation. $R^2 = 0.18$
Nicholls et al., 2007	CIRP	Compare STEM to non-STEM student with CIRP variables	Predictors for STEM students were SAT Math, high school grades, self-ratings of math ability, academic ability, scientific orientation, going to college to get training for a specific career. Predictors for Non-STEM students were likelihood of changing a major field or career and participating in a study abroad program.

Table 1. Review of literature.

the SAT Math to be a significant predictor. In previous research, Veenstra and Herrin (2006) found that the ACT Math test was a better predictor of a passing grade in the freshman courses at the University of Michigan. As a result, there was interest in comparing the ACT test variables with the SAT test variables as predictors. Because of the high percentage of students who took both the ACT and SAT tests, two separate subsets were created. The first subset contained the records of students who reported their ACT scores and the second subset contained the records of students who reported their SAT scores. In addition, the Levin and Wyckoff (1988) study showed that the math and chemistry placement tests were significant predictors for first year GPA. Correspondingly, the University of Michigan (UM) math and chemistry placement test scores were considered as variables.

A literature review prior to this study compared engineering education literature to the education literature (Veenstra, Herrin, and Dey, 2007). The literature review showed some differences between the two education fields. The SAT Math tends to be a predictor more for the engineering academic success studies and the SAT Total for education studies. Likewise, self-rating of math ability or confidence in engineering abilities tends to occur as predictors in engineering education studies and self-rating of overall academic ability tends to be a predictor in education (general college) retention studies. Because of these differences, the study was designed to compare Engineering students to three non-Engineering student sectors:

- Pre-Med students.
- The STEM disciplines (Science, Technology, Engineering and Math). For purposes of having independent samples among the student sectors, the STEM student sector excludes the Engineering and Pre-Med sectors.
- The Non-STEM disciplines. This sector focuses on the social sciences, arts and humanities majors.

The Pre-Med sector was chosen as another student sector with a high orientation towards science and a professional career. Therefore, it was hypothesized that the pre-college characteristics of the Engineering sector would be close to the Pre-Med sector because both were motivated towards a particular profession in the sciences. It was expected that the highest similarity in pre-college characteristics would be between the Engineering and STEM sectors. The greatest difference in the pre-college characteristics would be expected between Engineering and the Non-STEM student sectors.

This research study was guided by three research questions:

1. Are there significant differences in the pre-college characteristics between Engineering and other student sectors?
2. How well do the selected pre-college characteristics predict freshman academic success within each sector?
3. Do the ACT test or SAT test scores give better predictiveness of freshman engineering academic success?

Data on pre-college characteristics were obtained from the UCLA Cooperative Institutional Research Program (CIRP) survey; these data were merged with freshman performance data, including the freshman first year GPAs. Multiple comparisons were used to compare the average of the pre-college characteristics among the student sectors. Factor analysis and regression were conducted to predict freshman academic success and examine the relationships between the student sectors. A comparison was made between the predictability of the first year GPA of engineering students using the ACT-based characteristics and SAT-based characteristics.

II. Methodology

A. Data

This study was limited to first time, full-time students, whose freshman classes matriculated in the fall of 2004 or 2005 at the University of Michigan. For this group of students, data from the CIRP survey and student performance data were collected. The CIRP data included responses to the CIRP survey, including high school activities, goals for education and future career, self-ratings on academic and social characteristics, importance of coming to college, financial concerns about college expenses, and future college activities. The student performance data included high school GPA and class rank, ACT/SAT test scores, placement scores, number of credit units and term GPA.

During freshman orientation, all incoming students were invited to participate in the CIRP survey; this survey was administered by the Division of Student Affairs at the University of Michigan. Consistent with the IRB approval of this research, the analysis database included only data from students who gave permission for their data to be included in this research. All personal identifiers were removed from the data. After the subset of students who gave permission for their data to be used was established, the Division of Student Affairs and the Registrar's Office coordinated efforts to merge the CIRP data and the student performance data into the final research database. The response rates for the CIRP survey were 75 percent for both the 2004 and 2005 freshman class cohorts (Matney, 2005, 2006). Based on the full-time students who gave permission for their CIRP data to be included in this research, the effective sample rate compared to the total freshman class was 27 percent for the 2004 cohort and 33 percent for the 2005 cohort.

The SAT and ACT scores in the survey sample are consistent with the very selective admissions of the University of Michigan. The SAT Total 50 percent Mid-Range for the 2004 survey sample was 1200-1400 with a sample size of 1650. This sample mid-range is consistent with the SAT Total 50 percent Mid-Range of 1210 to 1400 for the entire 2004 student class cohort (University of Michigan, 2007). The 50 percent mid-range represents the difference between the 75th percentile and the 25th percentile. Both the SAT and ACT tests are well represented in the data. In the 2004 cohort, 64 percent of the students reported the SAT test results and 76 percent of the students reported the ACT test results.

B. Variables

Table 2 displays the pre-college characteristics included in this study; these characteristics were used to predict the first-year GPA. These pre-college characteristics were selected to represent nine broad categories related to student academic success. These categories will be referred to as pillars (P) of student success (Cokeley et al., 2006). In Table 2, note that both P1 (High School Academic Achievement) and P2 (Quantitative Skills) are divided into two subsets: the first with ACT test variables and the second with SAT test variables.

C. Student Sector Definitions

In order to compare the modeling of Engineering student success to the three non-Engineering sectors: Pre-Med, STEM, and Non-STEM, definitions of each sector were developed. The Engineering and Pre-Med student sectors were defined using the admitting college and the CIRP variable, Student's Probable Career. All students admitted to the College of Engineering were included in the Engineering sector. (At the University of Michigan, freshmen are admitted directly to the College of Engineering.) All students who indicated a probable career of a Physician (code 31 in the CIRP survey) were included in the Pre-Med sector.

The STEM and Non-STEM student sectors were defined using the CIRP variable Student's Probable Major. Although, "STEM" is used extensively in the literature, it was found that the definition of STEM was not universal or consistent, especially with respect to health technology and pre- professional majors (Nicholls, 2007); Likewise, the definition of Non-STEM was not consistent. The definitions used in this research were based on Nicholls' research, a review of the literature, and a review of the college curriculum for health technology and architecture majors.

In the STEM student sector, the following majors were included: science, math, computer programming/science, forestry, architecture, health technology, nursing, pharmacy, and dentistry and veterinary

Pre-college Characteristics
P1. High School Academic Achievement
High school GPA (corrected for non-significant courses)
High school class rank
ACT Composite*
SAT Total**
Self-rating of academic ability
Self-rating of leadership ability
Self-rating of self-confidence (intellectual)
P2. Quantitative Skills
ACT Math score*
SAT Math score**
ACT Science score*
UM math placement test score
UM chemistry placement test score
P3. Study Habits
Hours per week in the past year spent studying/ doing homework
Hours per week in the past year spent talking with teachers outside of class
Frequency of studying with other students
Frequency of asking a teacher for advice after class
Frequency of coming late to class
Frequency of feeling overwhelmed by all a student had to do
Chance in the future will communicate regularly with your professors
P4. Commitment to Career and Educational Goals
Highest academic degree that you intend to obtain
Importance in deciding to go to college: to get training for a specific career
Importance in deciding to go to college: to prepare for graduate or professional school
Importance in deciding to go to college: to be able to make more money
Chance in the future will change major field
Chance in the future will change career choice
P5. Confidence in Quantitative Skills
Self-rating of mathematical ability
Self-rating of computer skills
P6. Commitment to this College (U-M)
What choice is this college?
To how many other colleges other than this one did you apply for admissions?
Importance of coming to this college: college has good academic reputation
Importance of coming to this college: college has good reputation for social activities
Importance of coming to this college: rankings in national magazines
Importance of coming to this college: college's graduates get good jobs
Importance of coming to this college: offered financial assistance
Importance of coming to this college: not offered aid by first choice

Table 2: Pre-college characteristics.

Pre-college Characteristics
P7. Financial Needs
Concern about ability to finance college education
How much of first year's educational expenses are expected to be from loans?
P8. Family Support
Education level of father
Education level of mother
P9. Social Engagement
Self-rating of social self-confidence
Hours per week in past year socializing with friends
Hours per week in past year playing video/computer games
Hours per week in past year partying
Hours per week in past year doing volunteer work
Hours per week in past year in student clubs/groups
Chance in the future will join a social fraternity or sorority
Chance in the future will participate in student clubs/groups
Chance in the future will participate in a study abroad program

Note: * indicates characteristic is used in ACT subset only;
** indicates characteristic is used in SAT subset only.

Table 2. (Continued).

medicine majors. In the Non-STEM sector, the following majors were included: art, music, humanities, social sciences, business, education, kinesiology, and therapy majors.

D. Multiple Comparisons

One of the objectives of this empirical research was to determine if the engineering students have a different multivariate cluster of pre-college characteristics than the other student sectors (Pre-Med, STEM, and non-STEM). Pairwise multiple comparisons were made of the Engineering student sector average compared to the average of each of the three non-Engineering student sectors. The analysis used the SPSS 15.0 One-Way Analysis of Variance combined with the Sidak multiple comparison technique. The Sidak test is a modified Bonferroni test. The Bonferroni multiple comparisons adjusts the type I error for a particular comparison so that the family type I error for all multiple comparisons is no more than the specified error, usually 0.05. The Sidak multiple comparison technique has a higher power than the traditional Bonferroni test (Matthews, 2005). The family Type I error was set at 0.05.

E. Factor Analysis and Regression Analysis

Nine factor analyses were conducted; one for each pillar of student success. Table 2 lists the final set of pre-college characteristics included for each factor analysis. SPSS 15.0 for Windows was used with the Principal Axis Factor method to extract the factors. The Varimax method performed an orthogonal rotation of the factors and the Anderson-Rubin method was used to estimate the factor score coefficients such that the factor scores are scaled to an average of zero with zero correlation between the factor scores (SPSS Inc., 2006).

The Minitab best-subset regression and stepwise regression were used together to determine the best set of predictors for first year success (GPA) for each student sector. The adjusted R^2 value, Mallow's Cp statistic and residual standard deviation were considered in the final regression. The Mallow's Cp statistic indicates the amount of bias in the estimate of the regression coefficients. If important variables are left out of a prediction, bias will be present in the regression coefficients. With unbiased estimates, the *Cp* is equal to the number of predictors (Myers and Montgomery, 2002). In addition, multicollinearity was checked with the Variance Inflation Factor (VIF) statistic for each coefficient. A guideline for significant multicollinearity affecting the regression estimates is a VIF greater than four (Myers and Montgomery, 2002). The initial probability of the F to enter was set at 0.15 for the stepwise regression with the final regression requiring a significance level of 0.05 or less for each predictor. Separate regressions were run for the ACT and SAT subsets. Records with missing data in the factors were deleted from the analysis database.

III. Results

A. Significant Pairwise Comparisons among Student Sectors

Table 3 displays the significant multiple comparisons in the pre-college characteristics between the Engineering student sector and each of the other student sectors for the 2004 cohort. These comparisons represent the average differences in a characteristic as students enter their freshman year.

In comparing the Engineering sector to the non-Engineering sectors, the most significant differences were in the pillars of P1 (High School Academic Achievement), P2 (Quantitative Skills) and P5 (Confidence in Quantitative Skills). Significantly, there were no differences in P6 (Commitment to this College), P7 (Financial Needs) or P8 (Family Support); indicating that the Engineering sector perceived the same average level of commitment to the university, financial need, and family support as the other sectors.

The Engineering student sector displayed significantly higher average ACT Math, ACT Science, and ACT Composite,

Pre-college Characteristics	Engineering vs. Pre-Med	Engineering vs. STEM	Engineering vs. Non-STEM
P1. High School Academic Achievement			
High school GPA			H
High school class rank			H
ACT Composite	H	H	H
SAT Total		H	H
Self-rating of academic ability			H
P2. Quantitative and Analytical Skills			
ACT Math score	H	H	H
SAT Math score		H	H
ACT Science score	H	H	H
U-M math placement test score	H	H	H
U-M chemistry placement test score	H	H	H
P3. Study Habits			
Hours per week in past year spent studying/ doing homework	L		
Frequency of asking a teacher for advice after class	L		L
Frequency of feeling overwhelmed by all a student had to do	L	L	L
P4. Commitment to Career and Educational Goals			
Highest academic degree that you intend to obtain	L		
Importance of deciding to go to college: to get training for a specific career			H
Importance of deciding to go to college: to prepare for graduate or professional school	L		
Chance in the future will change major field			L
Chance in the future will change career choice			L
P5. Confidence in Quantitative Skills			
Self-rating of mathematical ability	H	H	H
Self-rating of computer skills	H	H	H
P9. Social Engagement			
Hours per week in past year playing video/computer games	H	H	H
Hours per week in past year partying			L
Hours per week in past year doing volunteer work	L		
Chance in the future will participate in a study abroad program		L	L

Note; H indicates that the Engineering sector average is higher in the pairwise comparison;
L indicates that the Engineering sector average is lower in the pairwise comparison

Table 3. Significant differences in averages of pre-college characteristics.

compared to the other student sectors. The Engineering sector also had significantly higher average self-ratings in mathematical ability and computer skills, indicating a higher confidence in quantitative skills. In the P3 (Study Habits) pillar, the Engineering sector averaged a significantly lower level of "feeling overwhelmed" than the other student sectors. With respect to P9 (Social Engagement), there were only a few significant differences between the Engineering student sector and the other sectors. The Engineering sector spent significantly more time playing video games than the other student sectors. In addition, the Engineering sector had less anticipation of participation in a study abroad program than the STEM and Non-STEM sectors.

Both Engineering and Pre-Med students were focused on a specific career, and there was no significant difference in the career-related question concerning going to college to prepare for a specific career. The Pre-Med students displayed a stronger motivation with a significantly higher average for earning a higher degree and going to college to prepare for a graduate or professional program. The Pre-Med students also displayed a higher average on the number of hours per week studying or doing homework, and for participating in volunteer work than Engineering students.

The comparisons of the Engineering sector to the STEM sector showed the least number of significant differences. Most of the differences were related to the Engineering sector having a higher average score for the ACT Math, ACT Science, SAT Math, math and chemistry placement tests, and self-ratings of mathematical ability and computer skills.

The highest number of significant differences occurred between the Engineering sector and Non-STEM sector. In addition to the Engineering sector having significantly higher averages for the ACT and SAT Math scores and self-ratings of mathematical ability and computer skills, the Engineering sector averaged a significantly higher high school GPA and class rank. On career choice issues, the Engineering sector attached a higher importance of going to college to pursue a specific career and had a lower chance of changing majors or careers. On the other hand, the Non-STEM sector showed a higher frequency of asking a teacher for advice. In socializing, the Non-STEM sector averaged more time in high school partying with their friends, while the Engineering sector averaged more time playing video and computer games.

B. Factor Analysis

A factor analysis was conducted within each pillar of student success to minimize the multi-collinearity among the regression predictors and to reduce the dimensionality of the number of predictors. Table 4 lists the factors, with labels given to each factor for the dimension it represents. Because a student could take the ACT or SAT tests, the ACT and SAT subsets were considered separately. Note that P1 (High School Academic Achievement) and P2 (Quantitative Skills) have separate ACT and SAT factor components.

C. Regression Analysis

Tables 5 and 6 display the stepwise regression results for the Engineering sector. Table 5 is an overview that compares the regression of the ACT factor subset to the regression with the SAT factor subset using the 2004 cohort. The goodness of fit criterion, as measured by the adjusted R^2 value, is within 0.01 for both subsets, indicating the same level of prediction. In applying this prediction equation as a cross-validation sample to the 2005 cohort, the ACT subset predictors gave a much larger adjusted R^2 value, indicating a better fit.

Table 6 displays each step of the stepwise regression using the Engineering sector data for both the ACT and SAT subsets. For both regressions, F4 (Quantitative Skills) was the first factor to enter the regression. For the ACT subset, it explained 23 percent of the total variation in the first year GPA. This factor included the ACT Math, ACT Science and the University of Michigan's math and chemistry placement test scores. Significantly, there was an interaction effect between the factors F1 (High School Grades) and F4 (Quantitative Skills). Based on the order in which the interaction entered the stepwise regression, this interaction was much stronger for the ACT subset than for the SAT subset. Overall, the R^2 values show that 37–38 percent of the variation of first year GPA was explained by pre-college characteristics, most of which was associated with academic preparation pillars, P1 (High School Academic Achievement), P2 (Quantitative Skills) and P5 (Confidence in Quantitative Skills).

F10 (Career Goals) entered in both regressions with a negative coefficient. It increased the adjusted R^2 value by less than 0.02, but was statistically significant. Its inclusion decreased the bias in the regression coefficients as indicated by the Cp statistics and therefore, was included in the regression. For an unbiased estimate of the coefficients, the Cp should be approximately equal to the number of predictors. In the case of the ACT subset, Cp equals 6.2, which is close to a value of 5, for five predictors. The correlation between F10 (Career Goals) and first year GPA was 2 0.132 (t-test significant with a $p = 0.022$). This factor included the variables, importance of going to college to get training in a specific career, to make money, and to prepare for graduate/professional school. Examination of the scatter plots of the data showed that the group of students, who assigned a low importance to going to college to get training or to make money, also had a very high average first year GPA. This created the negative correlation between the factor and the first year GPA.

For comparison purposes, using the ACT subset of the 2004 cohort database, stepwise regressions were conducted on the three non-Engineering sectors. Table 7 displays a comparison of the significant predictors. Note that the b coefficients are the unadjusted regression coefficients. The only common significant factor among the four sectors is F1 (High School Grades). The factors that are significant for the non-Engineering sectors are different from the factors that are significant for the Engineering sector. For all three of the non-Engineering sectors, F2 (High School Performance) is very significant ($p = 0.000$). F2 (High School Performance) is the factor for overall academic ability as measured by the ACT Composite and self-rating of academic ability. In contrast, for the Engineering sector, F4 (Quantitative Skills), as measured by the math and science scores and the interaction effect of F4 with F1 (High School Grades) were more significant as predictors. Although, by itself, F2 (High School Performance) was a significant predictor for the Engineering sector, once F4 (Quantitative Skills) was entered, F2 (High School Performance) contributed less than an additional 0.01 to the adjusted R^2 value. The adjusted R^2 values indicate that the percent of variation in the first year GPA explained by the predictors was substantially greater for the Engineering sector's regression than for the non-Engineering sectors' regressions. The adjusted R^2 value for the Engineering sector was 0.38 compared to 0.15 for the Pre-Med sector, 0.27 for the STEM sector and 0.26 for the Non-STEM sector. This supports the view that the selection of variables

Student Success Pillars and Factors	Pre-college Characteristics included in each Factor
P1. High School Academic Achievement	
F1 High School Grades	High school GPA High school class rank
F2 High School Performance	ACT Composite for ACT subset OR SAT Total for SAT subset; Self-rating of academic ability
F3 High School Leadership	Self-rating of leadership ability Self-rating of self-confidence (intellectual)
P2 . Quantitative Skills	
F4 Quantitative Skills	ACT Math, ACT Science for ACT subset OR SAT Math for SAT subset; math and chemistry placement test scores
P3. Study Habits	
F5 Study Habits-Communicate With Professors	Frequency of asking a teacher for advice Hours/week talking with teachers Chance will communicate with professors
F6 Study Habits-Homework	Hours/week studying/homework Frequency of feeling overwhelmed Frequency of studying with other students
F7 Study Habits-Class Attendance	Frequency of coming late to class
P4. Commitment to Career and Educational Goals	
F8 Choice of Major and Career	Chance will change major field Chance will change career choice
F9 Educational Goals	Highest academic degree aspiration Importance of decision to go to college: To prepare for graduate/professional school
F10 Career Goals	Importance of decision to go to college: To get training for a specific career To be able to make more money
P5. Confidence in Quantitative Skills	
F11 Confidence in Quantitative Skills	Self-rating of mathematical ability Self-rating of computer skills
P6. Commitment to this College	
F12 Goals-UM Reputation	Importance in choice of this college: Graduates get good jobs Rankings in national magazines Academic reputation Social reputation
F13 Goals – UM Choice	Choice of this college Number of other applications to colleges
F14 Goals – UM Financial Aid	Importance of choice of this college: Not offered financial aid by first choice Offered financial aid

Table 4. Factors and associated characteristics.

Student Success Pillars and Factors	Pre-college Characteristics included in each Factor
P7. Financial Needs	
F15 Financial Needs	Concern about financial aid Amount of loans for freshman year
P8. Family Support	
F16 Family Support	Parents' education level (maximum of either parent)
P9. Social Engagement	
F17 Social Engagement-Socializing	Hours/week partying Hours/week socializing with friends Chance will join social fraternity or sorority Self-rating of social self-confidence
F18 Social Engagement-Volunteer	Hours/week in student clubs/groups Hours/week doing volunteer work
F19 Social Engagement-Activities	Chance will participate in a study abroad program Hours/week playing video/computer games Chance will participate in student clubs

Table 4. (Continued).

Subset	Number of Predictors	Adjusted R^2 (2004 Cohort)	Cp (2004 Cohort)	Validated Adjusted R^2. (2005 cohort)
ACT subset	5	0.38	6.2	0.36
SAT Subset	6	0.37	6.6	0.17

Table 5. Stepwise regression results.

ACT Subset		SAT Subset	
Predictor	**Adjusted R^2**	**Predictor**	**Adjusted R^2**
F4(Quantitative Skills)	0.23	F4(Quantitative Skills)	0.18
F1 × F4 Interaction	0.33	F1(High School Grades)	0.28
F1(High School Grades)	0.35	F2(High School Performance)	0.32
F11(Confidence in Quantitative Skills)	0.37	F7(Study Habits- Class Attendance)	0.34
F10 (Career Goals)	0.38	F10(Career Goals)	0.36
		F1 × F4 Interaction	0.37

Table 6. Stepwise regressions: predictors listed in the order they entered the regression.

Significant Factors	Engineering		Pre-Med		STEM		Non-STEM	
	β	*p*-level	*β*	*p*-level	*β*	*p*-level	*β*	*p*-level
Constant	2.921	0.000	3.123	0.000	3.268	0.000	3.319	0.000
F1 High School Grades	0.113	0.004	0.152	0.025	0.189	0.001	0.106	0.000
F2 High School Performance			0.164	0.000	0.176	0.000	0.171	0.000
F4 Quantitative Skills	0.233	0.000						
F6 Study Habits-Homework					0.108	0.001		
F10 Career goals	-0.087	0.019						
F11 Confidence in Quantitative Skills	0.096	0.017						
F15 Financial Needs					-0.082	0.028		
F17 Social Engagement - Socializing					0.108	0.008		
F19 Social Engagement -Activities			0.114	0.049			0.097	0.000
F1 × F4	0.205	0.000						
F2 × F19							0.062	0.024
Number of cases	184		100		145		206	
Adjusted R^2	0.38		0.15		0.27		0.26	
Mallow's Cp	6.2		2.5		5.9		4.1	
Maximum VIF	1.193		1.014		1.066		1.025	

Table 7. Stepwise regression coefficients and significance levels (p-level for t-test) for each sector.

Statistic	Engineering		Pre-Med		STEM		Non-STEM		All Sectors	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
N	48	135	67	32	81	64	125	79	321	310
Average	3.064	3.166	3.096	3.182	3.293	3.248	3.324	3.288	3.230	3.216
Standard Deviation	0.542	0.548	0.540	0.412	0.530	0.419	0.415	0.485	0.503	0.495
	URM	Non-URM	URM	Non-URM	URM	Non-URM	URM	Non-URM	URM	Non-URM
N	20	155	7	91	13	124	19	175	59	545
Average	2.793	3.174	2.833	3.145	3.027	3.302	3.178	3.310	2.973	3.242
Standard Deviation	0.481	0.546	0.732	0.481	0.579	0.465	0.499	0.431	0.553	0.486

Table 8. Descriptive statistics of the first year GPA by gender and ethnicity.

for the engineering academic success model fit the engineering sector data better than for the other sectors.

D. Comparison by Gender and Ethnicity

Table 8 displays the average and standard deviation for the first year GPA by gender and ethnicity for the ACT subset. Because of the small sample sizes, ethnicity is summarized by Under-Represented Minorities (URM) and Non-Under-Represented Minorities (non-URM). URM students include students whose race is Black, Hispanic or Native American. Non-URM students include students whose race is White or Asian. The percent of female students was substantially less for the Engineering sector than for the other sectors. The percent of URM students was relatively constant (7 to 11 percent) across the four sectors. A *t*-test analysis showed that there was no significant difference in the average first year GPA by gender. Apparent GPA differences between URM and Non-URM students were attributable to preparation covariates in the regression models. No significant differences were observed after adjusting for these covariates.

IV. Discussion

A. Comparisons with Other Studies

In general, the predictors for freshman academic success were consistent with previous studies on engineering academic success. The multiple comparison differences between the Engineering sector and the Non-STEM sector were generally consistent with the findings of Nicholls' research on the differences between STEM and non-STEM groups (Nicholls et al., 2007). Consistent with the previous studies on engineering student academic success that showed that the SAT Math score was a significant predictor (see Table 1), the factor F4 (Quantitative Skills) was highly significant. In addition, F1 (High School Grades) which included the high school class rank was significant in this study. This finding is consistent with the Besterfield-Sacre, Atman, and Shuman (1997) study, in which the high school class rank was found to be a significant predictor for the first term GPA. F11 (Confidence in Quantitative Skills) was also significant in this study. Similarly, the Besterfield-Sacre, Atman, and Shuman (1997) study showed that students who liked math and science tended to have a higher first term GPA.

The percent of variation explained by the pre-college characteristics is higher than for other studies. Using the adjusted R^2 values, the pre-college characteristics explained 38 percent of the total variation in the first year GPA for the ACT subset. This compares to 21 percent for the Levin and Wyckoff (1988) study and 29 percent for the Besterfield-Sacre, Atman, and Shuman (1997) study.

B. Significant Interactions as Predictors

In this study, it was hypothesized that interactions among the significant predictors could contribute to a higher percent of the variation being explained. In fact, this was the case. The interaction of F1 (High School Grades) 3 F4 (Quantitative Skills) was highly significant (*p* 5 0.000) for the ACT subset and entered the stepwise regression as the second predictor. The magnitude of the coefficient for the interaction was the same as for the F1 (High School Grades) and F4 (Quantitative Skills). Thus, the inclusion of the interaction term predicts a higher first year GPA. For the Non-STEM student sector, the significance of the F2 (High School Performance) 3 F19 (Social Engagement-Activities) interaction suggests that overall academic preparation and social involvement activities contribute to a higher first year GPA. In summary, inclusion of the interactions in the regression model improved the fit of the data to the model, and improved the percent of explained variation as measured by the adjusted R^2 value.

C. How are Engineering Students Different?

With the research questions developed in this study, it was hypothesized that the averages of the pre-college characteristics of the Engineering sector students would be different from that of non-Engineering sector students and the significant predictors for the first year GPA would also be different. This empirical study supported these hypotheses as follows:

1. As they entered their freshman year, the Engineering sector students showed a significantly higher average level of quantitative skills using the ACT Math, ACT Science, and SAT Math scores (see Table 3). The multiple comparison tests confirm that the Engineering sector students were admitted to the College of Engineering with higher scores in math proficiency; in addition, their average science preparation and confidence in their abilities were significantly higher. This supports the premise that on average, engineering students are predisposed to analytical thinking as they enter their first year of college and are confident in their analytical abilities.
2. The regression results (Tables 7) showed that the Engineering sector had both common and unique predictors of first year academic success compared to the other student sectors. F1 (High School Grades), which included the high school GPA and class rank, was a common predictor for all four student sectors. However, F4 (Quantitative Skills) was significant as a predictor for first year GPA only for the Engineering student sector. In fact, F4 (Quantitative Skills) explains 23 percent of the total variation in the first year GPA for the Engineering sector. In addition, F11 (Confidence in Quantitative Skills) was significant only for the Engineering sector.
3. Interestingly, the social engagement factors were not significant predictors for the Engineering sector, but highly significant for the prediction of first year success for the non-Engineering sectors. This strongly suggests that while some college retention theories suggest that social engagement is an important element in predicting student success for the general college population, and in particular, for the Non-STEM student sector, it may be less important for Engineering sector students in the first year, where academic preparation in math and the sciences carries more weight.

   While there may be predictive differences, the data also show that the Engineering sector students, on average, are just as socially engaged as students in the other sectors. Of the nine social engagement variables listed in Table 2 (Pre-college characteristics), only four variables are listed in Table 3 with a significant difference in the average value between the Engineering sector and the other sectors. In particular, there was no significant difference in the averages for the variables: Self-rating of social self-confidence, Hours per week in past year socializing with friends and Hours per week in past year in student clubs/groups. Of the social engagement variables listed in Table 3, only Hours per week in past year playing video/computer games was significant for the Engineering sector compared to all other sectors. This tends to indicate a common level of social engagement across all sectors. Thus, the data tends to support that the difference in the significance of social engagement in predicting academic success is not due to a lesser level of social engagement in the Engineering sector, but rather other educational processes.
4. With respect to career choice, the Engineering and Pre-Med sector students differed from STEM and Non-STEM sector students in that their commitment to their career choice was very high, with a relatively low self-rated chance of changing major or career. They also considered it very important to go to college to get training for a specific career.

V. Conclusions

Freshman engineering success can be viewed as a process that is dependent on both the students' experiences before and during college. This study looked at the effect of pre-college characteristics on student academic success as measured by first year GPA.

For the Engineering student sector, the regression results strongly support the prediction of the first year GPA from the factors loaded with: the high school GPA and rank, the math and science test scores, and confidence in math and computer skills. In this study, 38 percent of the variation in first year GPA for engineering students is explained by their pre-college characteristics, underscoring the importance of high school preparation in explaining first year GPA.

As students enter college, the significant differences between Engineering and the other student sectors considered here were related to confidence in math and computer skills, actual math and science knowledge/skills, and career goals (Table 3). There were no significant differences for questions related to commitment to the college the student is attending, financial need concerns, or parents' education. Few significant differences in the average of the social engagement variables were present between the Engineering sector and the other sectors. Despite the stereotypical image of the engineer as a "nerd," the findings of this study support the image of an engineering student as socially well-rounded.

For the student sectors outside of engineering, this study supports the prediction of freshman academic success with F2 (the ACT Composite and self-rating of academic ability), and F1 (High School Grades). This finding supports that overall academic knowledge and ability is important for academic success for these sectors. This is consistent with the meta-analysis results on college GPA reported by Lotkowski, Robbins, and Noeth (2004).

Although engineering is understandably an important subset of the STEM disciplines, this study suggests that the predictors of freshman success are different for the Engineering sector and non-Engineering STEM sector students. The predictors for academic success for the STEM sector students were closer to that of the Non-STEM sector students than the Engineering student sector. For the STEM student sector, overall academic ability as measured by F2 (High School Performance) was significant for academic success; this factor was also significant for the Non-STEM sector. Neither F4 (Quantitative Skills), which measures quantitative and analytical skills nor F11 (Confidence in Quantitative Skills) were significant predictors for academic success for the STEM student sector. As previously discussed, these two factors were highly significant for the Engineering sector. This suggests that different strategies for student success are needed for Engineering sector students than for STEM sector students.

Consistent results were obtained with the ACT and SAT subsets. In most previous engineering academic success (GPA) studies, the SAT test scores were used as predictors. The analysis in this study suggests that the ACT test scores should be considered as just as predictive as the SAT test scores.

In modeling academic success (first year GPA), the regression results on the Engineering sector show that only a handful of the considered variables were important predictors. Excellent high school preparation in math and science and confidence in math and computer abilities is more important than the overall high school academic achievement as measured by the ACT Composite or SAT Total scores. This study adds to other studies that indicate that the modeling of engineering academic success is different from modeling of general college academic success.

Acknowledgments

The College of Engineering and the Rackham Graduate School of the University of Michigan provided support for this research. The authors wish to thank Dr. Malinda Matney of the Division of Student Affairs for her generous time and support and Andrew Cameron of the University of Michigan Registrar's Office for the development of the research database.

References

Astin, A., and H. Astin. 1992. Undergraduate science education: The impact of different college environments on the educational pipeline in the sciences. Sponsored by the National Science Foundation. Los Angeles: University of California, Los Angeles, Higher Education Research Institute.

Besterfield-Sacre, M., C. Atman and L. Shuman, 1997. Characteristics of freshman engineering students: Models for determining student attrition in engineering. *Journal of Engineering Education,* 86 (2): 139–49.

Burtner, J. 2004. Critical-to-quality factors associated with engineering student persistence: the influence of freshman attitudes. *34th ASEE/ISEE Frontiers in Education Conference (F2E-1).* Available at: http://fie.engrng.pitt.edu/fie2007/index.html.

Clough, G. 2004. *The engineer of 2020:* Visions of engineering in the new century. Washington, DC: National Academy of Engineering (NAE).

Cokeley, S., M. Brynes, G. Markley, and S. Keely, S., eds. 2006. *Transformation to performance excellence.* Milwaukee, WI: ASQ Press.

French, B., J. Immekus, W. Oakes. 2005. Research brief: An examination of indicators of engineering students' success and persistence. *Journal of Engineering Education* 94 (4): 419–25.

Levin, J., and J. Wyckoff. 1988. Effective advising: Identifying students most likely to persist and succeed in engineering. *Engineering Education* (December): 178–82.

Lotkowski, V., S. Robbins, and R. Noeth, 2004. The role of academic and non- academic factors in improving college retention. ACT, Inc., http://www.act.org/research/policymakers/pdf/college_retention.pdf (last accessed July 2008).

Matney, M. 2005. *College of engineering: Entering student survey 2004: Summary data from the Cooperative Institutional Research Program (CIRP).* Ann Arbor: University of Michigan Division of Student Affairs.

Matney, M. 2006. E-mail communication, April 20, 2006.

Matthews, P.G. 2005. *Design of experiments with Minitab.* Milwaukee, WI: ASQ Quality Press.

Myers, R. and D. Montgomery. 2002. *Response surface methodology (2nd ed.).* New York: John Wiley & Sons, Inc.

National Academy of Sciences (NAS). Committee on Science, Engineering, and Public Policy (COSEPUP). 2005. *Rising above the gathering storm: Energizing and employing America for a brighter economic future.* Washington, DC: The National Academies Press.

National Science Foundation. 2004. NSB science and engineering indicators report. Available at http://www.nsf.gov/statistics/seind04/.

National Science Foundation. 2006. NSB science and engineering indicators report. Available at http://www.nsf.gov/statistics/seind06/.

Nicholls, G. 2007. Draft of chapter 3 of Ph.D. dissertation, University of Pittsburgh.

Nicholls, G., H. Wolfe, M. Besterfield-Sacre, L. Shuman, S. Larpkiattaworn. 2007. A method for identifying variables for predicting STEM enrollment. *Journal of Engineering Education* 96 (1): 33–44.

Seymour, E., and N. Hewitt. 1997. *Talking about leaving: Why undergraduates leave the sciences.* Boulder, CO: Westview Press.

Shuman, L, M. Besterfield-Sacre, D. Budny, S. Larpkiattaworn, O. Muogboh, S. Provezis, H. Wolfe, 2003. What do we know about our entering students and how does it impact upon performance? In *Proceedings of the 2003 American Society for Engineering Education Annual Conference and Exposition, Session 3553.* Washington, DC: American Society for Engineering Education. Available at: www.asee.org.

SPSS Inc. 2006. SPSS 15.0 for Windows Software, Help Command.

University of Michigan. 2007. Freshman class profile, dated 1/17/2007, viewed at http://sitemaker.umich.edu/obpinfo, on 2/7/07.

Veenstra, C. and G. Herrin, 2006. Using the SAT and ACT scores for placement into engineering freshman classes. In *Proceedings of the 2006 American Society for Engineering Education World Conference, 2006–771.* Washington, DC: American Society for Engineering Education. Available at: www.asee.org.

Veenstra, C., G. Herrin, and E. Dey, 2007. Development of a freshman engineering retention model based on pre-college characteristics. *IOE Technical Report* 07-04. March 27. Available at: http://ioe.engin.umich.edu/techrprt/pdf/TR07-04.pdf .

Zhang, G., Y. Min, , M. Ohland, and T. Anderson, 2006. The role of academic performance in engineering attrition. In *Proceedings of the 2006 American Society for Engineering Education World Conference,* 2006–1336. Washington DC: American Society for Engineering Education. Available at: www.asee.org.

Authors' Biographies

Cindy P. Veenstra recently earned her Ph.D. in Industrial and Operations Engineering at the University of Michigan. The research discussed in this paper was part of her Ph.D. Her research interests are in applying quality engineering methodology and systems thinking to engineering education, especially to the retention of freshman engineering students. She also holds a M.S. in Statistics and a M.S. in Industrial and Operations Engineering. She is a member of ASEE, INFORMS, SME and an ASQ Fellow.

Address: Industrial and Operations Engineering, University of Michigan, 1205 Beal Ave., Ann Arbor, MI 48109-2117; telephone: (1 1) 734.355.7261; e-mail: cpveenst@umich.edu.

Eric L. Dey, Ph.D. is associate professor in the Center for the Study of Higher and Postsecondary Education at the University of Michigan School of Education. Dr. Dey's research is concerned with the ways that colleges and universities shape the experiences and lives of students and faculty. The central focus of this work is in identifying the influence that different institutional structures have on individuals, and the degree to which these influences are dependent on the evolving context within which the enterprise of higher education operates. As one example of this work, he was a member of the team of social scientists tapped to provide research on the educational effects of diverse student bodies; this work was foundational to the Supreme Court's decision supporting the continuing use of affirmative action in college admissions.

Address: Center for the Study of Higher and Postsecondary Education, University of Michigan, 2117G School of Education Building, Ann Arbor, MI 48109-1259; telephone: (1 1) 734.647.1651; e-mail: dey@umich.edu.

Gary D. Herrin, Ph.D., is professor of Industrial and Operations Engineering at the University of Michigan. He is a member of ASEE and IIE.

Address: Industrial and Operations Engineering, University of Michigan, 1205 Beal Ave., Ann Arbor, MI 48109-2117; telephone: (1 1) 734.763.0040; e-mail:gdherrin@umich.edu.