Engineering Technology Students: Factors Predicting Success

Gretchen A. Mosher

Iowa State University

Introduction to the problem

The published literature regarding students who depart engineering has generally not examined those who stay in the "T" part of STEM by pursuing engineering technology (ET). Internal data from the authors' department suggest that students who transfer into ET from engineering fields often succeed in the more hands-on setting, but bring with them far lower early-semester GPAs. Internal data also show that these transfers may have lower engagement with the discipline and less interaction with faculty and student organizations.

There is little investigation of students who leave engineering and pursue degrees in ET. The leaky pipeline to STEM professions is well known by researchers. However, the reasons students leave are less universal. Research on faculty perceptions of student persistence in STEM studies show study habits, commitment to educational goals, and family support as primary influencing factors [1], but other researchers report that the main reasons students depart from engineering and STEM fields are non-academic [2, 3, 4]. Furthermore, George-Jackson [4] reports that not all students who leave engineering leave STEM, and calls upon researchers to learn more about students who change majors within STEM fields.

Nearly three-quarters of ET students in the authors' department at Iowa State University transfer from engineering programs. Making students feel welcome in their new major and confident in their academic abilities has been a challenge for faculty and staff. Some students find ET to be an excellent fit for their skills and abilities while others continue to struggle academically – perhaps the lack of success with which they met early on in engineering make it difficult to be successful even when they matriculate into a "better fit" program. Addressing non-academic factors such as self-confidence, sense of belonging, and classroom climate are a first step in characterizing the challenge. Yet, little research has examined academic and non-academic factors that explain why some internal transfers successfully transition and others do not.

As ET programs nationwide struggle to recruit and retain graduate students and faculty, appropriate undergraduate preparation and early professional engagement in the field is critical [5]. For students in ET to transition into professional and faculty roles, engagement with professional organizations and professional development activities are significant. Promoting student success of undergraduates in ET is not only important in the short-term to ensure an adequate supply of technology professionals, but is also important for the long-term sustainability of the field of ET and the development of its future faculty.

The goal of this project was to identify and examine factors that influence success in students who enroll in and transfer into engineering technology programs. Factors were characterized as "academic predictors" and "curricular factors" for inclusion in the models. Academic predictors included variables such as high school rank and GPA, composite scores from the American College Test (ACT), mathematics scores from the ACT, and university GPA. Curricular factors included grades earned by students in several core ET courses.

The dependent variable for both sets of factors was a qualitative "seriousness of purpose" score assigned by senior capstone instructors. The "seriousness of purpose" score is based on attributes such as initiative with problem-solving, analytical competence, critical thinking, and project management in the open-ended problem-solving environment typical of a senior capstone course. Furthermore, the 6-credit hour capstone course is a key bridge from the ET classroom to the workplace and capstone performance is considered a critical predictor of success in the immediate post-graduation position. Approximately 115 students who graduated in 2014-2015 in industrial technology (ITEC) and agricultural systems technology (AST) were included in the analysis.

What's important about success in ET?

Engineering technology has not been a primary focus area in discussions of the future technical workforce in the United States [6]. This is true even though ET professionals play an important role in supporting and leading the technical infrastructure and innovation capacity in the U.S. The line between engineering and engineering technology is fuzzy and according to the National Academy of Engineering's (NAE) 2016 study, there is no widely accepted definition of ET.

The 2016 report by the NAE on Engineering Technology provided a comprehensive review of ET programs in the U.S. and made several recommendations. One of these was the need for a better understanding of why certain portions of the population graduate at higher rates in ET than others. A primary goal of this project was to examine early indicators influencing the success of ET students. A better understanding of these factors is expected to not only facilitate improvements in undergraduate ET programming, but to improve graduate education and faculty preparation in ET.

Student engagement with the profession of science and interest in the field has been found to have a higher association with retention and graduation than grade point [7, as cited by 2]. As ET programs nationwide struggle to recruit and retain graduate students and faculty, appropriate undergraduate preparation and early professional engagement in the field is critical [5]). For students in ET to transition into professional and faculty roles, engagement with professional organizations and professional development activities are significant. Promoting student success of undergraduates in ET is not only important in the short-term to ensure an adequate supply of technology professionals, but is also important for the long-term sustainability of the field of ET and the development of its future faculty.

Transfers between Engineering, STEM, and ET

Very little information is known about ET graduates and even less has been written about the academic pathway of these graduates [6]. Conventional wisdom attributes high attrition from engineering to other disciplines an unavoidable cost of under-prepared or unmotivated students entering engineering degree programs. As noted by [2] and others, not all those who exit the engineering discipline do so primarily because of low academic performance.

Several researchers have examined the career pathways of students who have left engineering and found success in other STEM disciplines [8, 9, 10] but largely absent from the published literature is specific information on students who transfer from engineering into ET. Ortiz and Sriraman [1] explored faculty perceptions on why students leave STEM fields, but ET students were a small portion of their sample. Faculty rated study habits, commitment to career and education goals, family support, and academic aptitude as primary factors in influencing student persistence in STEM fields [1], but the data were limited to one institution and may not be true for all ET students. Although some information on the outcomes of students who leave one STEM field for another has been published [1, 9] almost no information is available on factors influencing the success of those who transfer into a second STEM field.

Geisinger and Raman [2] point out the resource load of students leaving engineering and specify that exiting students have multiple costs at the individual, institutional, and societal levels. Furthermore, the authors assert when students leave the field for non-academic reasons, the losses are unacceptable. Kaleita et al. [11] expand on this idea by suggesting that identification of at-risk students at admission is not only feasible, but preferable when considering student efficacy and persistence in earning a college degree [12].

For students who have interest and aptitude in science and mathematics, but are not a good fit for engineering, ET provides a viable alternative. Like engineering, ET degree programs have a heavy emphasis in math, science, and design, albeit in a less theoretical and more applied manner than engineering [6]. Characterizing factors that influence the successful recruitment and retention of ET students has merit for the same efficacy and economic reasons as noted for engineering [2].

Anecdotal evidence from the authors' academic department suggests that ET students are not aware of the ET discipline when they enter the post-secondary system. Rather, they "discover" ET, with over 75% of transfer transferring from an engineering field. Some students enter the discipline with a semester or less in engineering, while others have nearly three years in engineering completed before making the switch. Some students transition very successfully into ET programs with little negative impact on GPA, while others bring low GPAs with them and continue to struggle with low academic performance, a disconnection to the ET field, and a lack of professional identity. Yet, little research has characterized academic and curricular factors that predict a successful transition into ET.

The approach and methodology for characterizing student risk factors employed by Kaleita et al. [11] provided the basis for this project. Two key factors differentiated this study from that of Kaleita et al. [11]. While Kaleita's team [11] examined risk factors for failure in engineering at a research-intensive institution, this project investigated factors which encouraged successful outcomes in students. A second difference was that this project looked specifically at students enrolled in engineering technology programs rather than those in engineering programs. Although no known empirical data support the hypothesis that success factors between engineering and ET students could be different, known characteristics about both fields of study and the students who enroll in these disciplines [6, 13] suggest success factors could differ.

To characterize the success factors that influence student outcomes in ET 4-year degree programs, the following research questions were addressed in this project:

1. What academic and curricular variables predict ET student GPA at graduation?
2. What are academic and curricular variables that predict ET student "seriousness of purpose" as defined by the senior capstone instructor?
3. What academic and curricular variables influenced student success in an ET undergraduate degree program?

Use of Multiple Linear Regression and CART Modeling

Predicting student success has traditionally utilized multiple linear regression (MLR), and this method was used to predict student success (defined as having GPA>2.8 at graduation). However, a binary classification method was preferable in this case, as primary project goal was to predict whether the student will be successful or not, rather than trying to predict the specific GPA he or she might earn. Further, MLR assumes Type 1 and Type II errors are approximately equal. When predicting student success, costs associated with a false negative (Type II) are much higher than those associated with a false positive (Type 1). In other words, the cost of missing an at-risk student is of greater concern than incorrectly classifying a student as being at-risk when he or she is not.

To address these challenges, a Classification and Regression Tree (CART) model was used to classify students as either "successful" or "not successful". A second advantage of the CART model was its ability to predict non-linear variables, including categorical variables. In this pilot research, the cost ratio (a measure specifying the penalty associated with missing or under-identifying an at-risk student) was defined as 1:1 [11]. In other words, Type I and Type II errors were equally undesirable. Future analysis will include cost ratios with greater weight on minimizing Type II errors.

Four total MLR models were generated. In the first set of models, the dependent variable "Seriousness of purpose" (SoP) was modeled against the "academic" variables of high school GPA, high school rank, composite ACT score, mathematics ACT score, and overall scores on the ALEKS math placement test, taken by entering freshmen. SoP was also modeled against "curricular" variables including three core courses in the ET degree programs: a freshmen-level problem-solving course (TSM 115); a sophomore-level introduction to technology course, introducing mathematical tools for data analysis (TSM 210); a junior-level total quality management course (TSM 310); and a senior-level capstone course (TSM 416). Seriousness of purpose was not modeled against TSM 310 because the same person teaches TSM 310 and capstone. Therefore, the independence of the seriousness of purpose assessment and the TSM 310 were not independent, making multicollinearity a high possibility. All independent variables were also modeled against each student's university GPA at graduation. The CART model analyzed academic and curricular variables that influenced student success as described below.

Regression and CART models were built using variables examined by previous predictive models on undergraduate success or failure [11, 13, and 14]. Data were analyzed using SPSS version 20 for MLR models and R for the CART model. The coefficient of determination (R^2) was used to evaluate the fitness of the MLR models. Standardized Beta coefficients and the standard error of each were also reported to characterize the role of each variable. The CART model separated students considered "successful" as those who were at the 51st percentile or above (GPA > 3.19). Students at or below the 50th percentile were considered "not successful" for the purposes of this analysis.

Results and Discussion

Traditional measures of prediction include information found on the college application and this information is often used in early advising and course selection [11]. Means, modes, standard deviations, ALEKS placement test scores, and minimum and maximum values for each are shown in Table 1.

Table 1. Descriptive data on academic variables used in analysis

Variable	Mean	Mode	S.D.	Minimum	Maximum
ACT Math Score	24.30	24	3.76	16	35
ACT Composite	23.30	22	3.11	14	32
High School GPA	3.50	3.33	0.298	2.68	4.00
High School Rank	72.39%	75	14.35%	30%	99%
ALEKS Score	52.41	63	22.08	10	92

N=109

Academic and curricular variables were modeled against two dependent variables, university GPA at graduation and a "seriousness of purpose" assessment from capstone instructors. Table 2 displays regression details from the MLR analysis conducted to answer research questions 1 investigating the influence of academic and curricular predictors of ET student GPA at graduation.

Table 2. Regression detail of GPA at graduation modeled with academic and curricular variables

Variable	R^2 coefficient	Std. Beta	Std. Error	P-value
ACT Math	0.259	-0.148	0.18	0.343
ACT Composite	0.364	0.176	0.176	0.253
High School GPA	0.571	0.427	0.427	0.003*
High School Rank	0.499	0.109	0.109	0.443
ALEKS Score	0.357	0.232	0.232	0.069
TSM 115 – 1st yr.	0.244	0.117	0.034	0.097
TSM 210 – 2nd yr.	0.541	0.289	0.038	0.000*

TSM 310 – 3rd yr.	0.688	0.558	0.059	0.000*
TSM 416 – 4th yr.	0.271	0.121	0.058	0.083

*significant at α=0.05

As is true in previous research [11, 13, and 14], high school rank significantly predicts ET student GPA and placement test scores show a weak prediction (not significant at α=0.05) for ET student success. A primary difference in ET data as compared with engineering and other STEM disciplines [11, 13, and 14] was the lack of a significant predictive relationship between student GPA and ACT composite and math scores. Although correlation values between traditional prediction factors and student GPA were moderately strong, the same variables were not found to be significant in the regression model, suggesting that these variables are not strong indicators of success for this group of ET students.

An additional difference in the ET data was the low predictive influence of a freshmen-level, discipline-specific course. The first-year GPA has been shown in several studies to have a strong predictive relationship with student success in STEM and non-STEM fields [13, 15]. With ET students, it appears the strongest predictive courses are completed in the sophomore and junior years. These are substantial differences from published literature in other disciplines and warrant further study with a larger sample of ET students.

While student GPA at graduation is a valid measure of how students perform in the classroom, not all learning is best measured by a graded, quantitative scale. To measure classroom performance in a "non-graded" way, the "seriousness of purpose" measure was conceptualized. The measure is intended to evaluate the student's ability to apply what he or she has learned in an open-ended and practical way. In engineering and ET fields, the senior capstone course is where theory and practice collide, so assessing students on their capstone performance is a logical way to measure classroom performance. The qualitative measure of "seriousness of purpose" provides an alternative way to measure both how well students have learned course content and how effectively they can use the content to solve realistic problems in ET.

Table 3. Regression detail of "Seriousness of Purpose" modeled with academic and curricular variables

Variable	R^2 coefficient	Std. Beta	Std. Error	P-Value
ACT Math	-0.006	-0.307	0.040	0.084
ACT Composite	0.140	0.152	0.044	0.383
High School GPA	0.529	0.557	0.0478	0.002*
High School Rank	0.410	-0.028	0.010	0.872
ALEKS Score	0.099	0.099	0.005	0.481
TSM 115	0.132	-0.008	0.107	0.938
TSM 210	0.379	0.348	0.114	0.001*
TSM 416	0.250	0.189	0.179	0.069

* significant at α=0.05

High school GPA played a significant predictive role with seriousness of purpose, but none of the other academic variables were consistent in the MLR. This finding confirms that academic predictors used effectively in engineering [11, 16] may not work as well for predicting success in ET students. Performance in the sophomore-level course also was significant in predicting a strong "seriousness of purpose" in ET students. A low correlation was also noted between seriousness of purpose and the senior-level capstone earned grade. The variables was weakly significant in the regression model (at α=0.10). The finding was surprising given anecdotal observations that student efficacy increases after students "find" ET and see academic success in the more applied coursework. Another obvious point is that the seriousness of purpose assessment is based on student performance in capstone, yet only a weak correlation is noted.

To further understand the role of academic and curricular variables in student success, a Classification and Regression Tree was constructed. The percentage of correct classification is also reported. In CART modeling, prediction error is measured as a misclassification, as explained in Kaleita et al. [11]. In this context, Type II errors are of greater concern than are Type I errors. Failing to identify a student who is predicted to be successful but does not actually realize success (a Type II error) is classified as a greater loss by Geisinger and Raman [2] and Kaleita et al. [11] than a student who has more intervention than necessary (a Type I error).

Two CART models were constructed. The first used university GPA at graduation as the dependent variable and did not include the variables of SoP or TSM 310 (because of the potential multicollinearity between the two variables). The first CART model identified the sophomore-level course (TSM 210), ACT composite scores, ACT math scores, and ALEKS placement test scores as the top four variables in the model that predicted the student's university GPA at graduation.

The second CART model also used university GPA at graduation as the dependent variable. Independent variables included all academic and curricular variables except TSM 310 (junior-level course). The analysis identified TSM 210 (sophomore-level course), the instructor's seriousness of purpose assessment, high school GPA, and the ALEKS math placement test scores as significant predictors of student GPA at college graduation.

Table 4. Importance of variables in predicting GPA at graduation

CART Model 1 – not including SoP	% variance	CART Model 2- including SoP	% variance
Variables		Variables	
TSM 210 (2nd yr. course)	33.08	TSM 210 (2nd yr. course)	45.91
ACT Composite	22.42	Seriousness of Purpose	29.55
ACT Math	11.75	High School GPA	9.32
ALEKS Score	10.37	ALEKS Score	5.46

The qualitative assessment of seriousness of purpose has been shown to explain a large portion of variance in student GPA at graduation. The student/instructor relationship in the senior capstone could explain some of the significance of the SoP variable. The capstone course is where student competencies are put to a test with an unstructured problem. When SoP is not included in the model, conventional predictors such as ACT and ALEKS scores play a larger role in explaining the variance in student GPA at graduation.

Specifically, the grade earned in the sophomore-level course (TSM 210) is significantly predictive in both models. Students who earn a "B" or better in TSM 210 have higher probabilities of success. High success is also likely when students have an above average SoP rating (3 or greater), suggesting that students who are willing to dedicate their resources to learning the introductory material at the sophomore level will see higher rates of success than those who do not. The freshmen-level course (TSM 115) does not seem to play a similar role in predicting student success. When student SoP is not considered in the model, ACT composite and mathematics scores become more important to the prediction.

Another important measure is the accuracy of the models. Total model accuracy is 91.9%, and the percentage of correct classifications in each model is shown in Table 5. The high rate of error in prediction noted in both models (approximately 22% incorrect classification of students who predicted to be successful but are not) suggests that important variables could be missing from the analysis.

Model	Predicted S Actually S	Predicted NS Actually NS	Predicted S Actually NS	Predicted NS Actually S
CART-1	96.74%	77.42%	22.58% (Type II)	3.26 (Type I)
CART-2	96.74%	77.42%	22.58 (Type II)	3.26 (Type I)

S= success; NS= non-success

Anecdotal observations suggest other variables may play a role in the success of ET students. Because of the high emphasis on applied and practical learning outcomes, many ET students feel their work experience is as valuable as their coursework [6], leading them to work a lot of hours. These work hours could be influencing the time they spend on academic coursework and on how successful they are in these endeavors. Student efficacy, or lack thereof, particularly from those who transfer from engineering, may also play a role in student confidence and motivation in academic matters. Finally, student attitudes toward the importance of theory versus that of applied practice, could impact student success in ET degree programs.

This paper specifically examines ET students who transfer into ET from another major. At Iowa State University, over 75 percent of students who enroll in ET are "internal transfers" from other majors. However, this is not the case at all universities who teach ET students. Many ET programs recruit students beginning at the high school level and this could influence factors predicting their success. For this reason, the data analysis and conclusions in this paper cannot be generalized to all ET students.

This research identifies potential factors that are significant in the success path of students who transfer into ET programs from engineering programs. The pilot research project identified several other factors warranting further examination. The importance of learning more about ET students and their undergraduate degree pathways has several implications. The loss of students from engineering should not be compounded by the loss of their skills, abilities, and potential to the STEM field. A better understanding of how students who transfer from "E" into "T" can help faculty mitigate losses in engineering [2]. Further, to continue to sustain and develop the ET profession in the future requires strong undergraduates who have an interest and aptitude for graduate school. Understanding success pathways of ET students allow faculty to take the first step in moving high ability ET students in this direction.

Acknowledgements: The author thanks D. Raj Raman, Morrill Professor, and Amy L. Kaleita, Associate Professor, both in Agricultural and Biosystems Engineering at Iowa State University for their input and guidance during this project.

References:

1. Ortiz, A.M. and V. Sriramen. Exploring faculty insights into why undergraduate college students leave STEM fields of study – A three-part organizational self-study. *American Journal of Engineering Education*, 6(1), 2015, pp 43-60.
2. Geisinger, B.N. and D.R. Raman. Why they leave: Understanding student attrition from engineering majors. *International Journal of Engineering Education*, 39(4), 2013, pp 914-925.
3. Marra, R.M., K.A. Rodgers, D.Shen, and B. Boogue. Leaving engineering: A multi-year single institution study. *Journal of Engineering Education*, 101(1), 2012, pp 6-27.
4. George-Jackson, C.E. STEM switching: Examining departures of undergraduate women in STEM fields. *Journal of Women and Minorities in Science and Engineering*, 17(2), 2011, pp 149-171.
5. Martin, G., J. Ritz, and M. Kosloski. Technology and engineering education doctoral students' perceptions of their profession. *The Journal of Technology Studies*, 40(2), 2014, pp 82-94.
6. National Academy of Engineering. *Engineering technology education in the United States*. K.G. Frase, R.M. Latanision, and G. Pearson, Eds. National Academies Press, Washington, D.C., 2016.
7. Grandy, J. Persistence in science of high-ability minority students: Results of a longitudinal study. *Journal of Higher Education*, 69(6), 1998, pp 589-620.
8. Ohland, M.W., G. Zhang, B. Thorndyke, and T.J. Anderson. *Grade-point average, changes of major, and majors selected by students leaving engineering*. Proceedings of the ASEE/IEEE Frontiers in Education Conference, Session T1G, Savannah, GA, October 2004.
9. Watkins, J. and E. Mazur. Retaining students in science, technology, engineering, and mathematics (STEM) majors. *Journal of College Science Teaching*, 42(5), 2013, pp 36-41.
10. McNeil, J.C., M.W. Ohland, and R.A. Long. *Entry pathways, academic performance, and persistence of nontraditional students in engineering by transfer status.* Proceedings of IEEE Frontiers in Education Conference, Erie, PA, October 2016.
11. Kaleita, A. L. G.R. Forbes, E. Ralston, J. Compton, D. Wohlgemuth, D.R. Raman. Pre-enrollment identification of at-risk students in a large engineering college. *International Journal of Engineering Education*, 32(4), 2016, pp 1647-1659.
12. Moller-Wong, C, M.C. Shelley, and L.H. Ebbers. Policy goals for educational administration and undergraduate retention: Toward a cohort model for policy and planning. *Review of Policy Research*, 16(3-4), 1999, pp 243-277.
13. Veenstra, C.P., E.L. Dey, and G. D. Herrin. Is modeling of freshman engineering success different from modeling of non-engineering success? *Journal of Engineering Education*, 59(1), 2008, pp 467-479.
14. Gansemer-Topf, A. M., J. Compton, D. Wohlgemuth, G. Forbes, E. Ralston. Modeling success: Using pre-enrollment data to identify academically at-risk students. *Strategic Enrollment Management Quarterly*, 3(2), 2015, pp 109-131.
15. Gansemer-Topf, A. M., A. Kollasch, and J. Sun. A house divided? Examining persistence for on-campus STEM and non-STEM students. *Journal of College Student Retention: Research, Theory, and Practice*, 19(2), 2017, pp 199-223.
16. French, B.F., J.C. Immekus, and W.C. Oakes. An examination of indicators of engineering students' success and persistence. *Journal of Engineering Education*, 94(4), 2005, pp 419-425.

GRETCHEN A MOSHER: Dr. Mosher is an assistant professor in Agricultural and Biosystems Engineering at Iowa State University. She leads the department's academic advising unit and holds a teaching and research appointment. Her research interests include continuous improvement methods in agricultural and food systems, use of data analytics to predict student outcomes, and use of decision-making to evaluate student learning.