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A structural equation model correlating success in engineering with academic variables for community college transfer students

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A STRUCTURAL EQUATION MODEL CORRELATING SUCCESS IN ENGINEERING WITH ACADEMIC VARIABLES FOR COMMUNITY COLLEGE TRANSFER STUDENTS

Abstract

Student Enrollment and Engagement through Connections is a collaboration between a large Midwestern university and in-state community colleges (CCs) to increase success of transfers into engineering. This study explores predictors of completing a BS in engineering for CC transfers through a structural equation model. The model was estimated using academic variables from both institutions. The dataset includes 472 in-state CC transfer students admitted to the College of Engineering between 2002 and 2005. The model fits the data well (χ^2=74.254, *df*=30, *p*<0.0001; RMSE=0.056, Comparative Fit Index=0.984, chi-square/*df* ratio=2.475). First spring University GPA and credit hours, CC transfer credits toward core engineering courses, first fall credit hours after transfer, first fall University GPA, and University core course GPA are significantly related to graduation in engineering. This research may help increase the success of CC transfers to engineering, emphasizing the importance of core engineering courses.

Introduction

This is an exploratory study to determine the strength of the relationships between core engineering coursework and graduation in engineering for community college (CC) transfer students. The longitudinal study accounts for the coursework taken at the CC prior to transfer as well as coursework taken at the University after transfer. The objective of the study is to create a structural equation model (SEM) to estimate the covariance structure based on hypothesized relationships between the academic variables and the outcome of graduation in engineering. The model provides a simultaneous analysis of relationships among the academic variables. The results of this study may be instructive to the CC administration, to academic advisors, and to students who are considering or already are pursuing a degree in engineering. . The purpose of this study, taken along with other informative qualitative studies, is to increase the success of CC transfers to engineering. This research could further increase both the number and diversity of engineering graduates and contribute to workforce development and national economic strength.

The model is developed based on academic and background variables for in-state CC transfer students who entered the College of Engineering at a large Midwestern State University (SU) during the fall semesters of 2002 through 2005. It follows CC transfer students longitudinally over a six-year period, allowing sufficient time for graduation. For these cohorts of students, 49% graduated in engineering. It is important to note that transfer students are defined by the institution they attended immediately following high school graduation and prior to transfer, and not by the number of credits transferred.

One problem in creating these models is obtaining data from both the sending and receiving institution. Unique in this study is the use of academic variables from both institutions. Other models based on academic integration variables have not included CC characteristics[1]. Nor have previous models been specific to graduation in engineering for CC transfer students. Taken together, these strategies provide a roadmap for success that proved to be influential for this sample of CC students.

Key variables in determining graduation are based on performance in core courses in engineering and first-year performance after transfer. These core courses are offered at both the sending and receiving institution. In this study the core courses are identified as the Basic Program (BP) in engineering. All students must successfully complete the BP with a minimum C average (2.0 on a 4.0 scale) to graduate in engineering. This program consists of two semesters of calculus, one semester of chemistry, one semester of physics, two semesters of English, and one semester of engineering fundamentals with computer programming. These courses represent the most substantial barrier to achieving an engineering degree[1,2,3].

Background

Recognizing the importance of increasing graduates in STEM fields, the National Science Foundation (NSF) has funded the Science Technology Engineering and Mathematics (STEM) Talent Expansion Program (STEP). One initiative of the STEP program is the Student Enrollment and Engagement through Connections (SEEC) project. SEEC is a collaborative, connection-based alliance between the SU and one of the in-state CCs. The purpose is to increase the success of CC transfers to engineering.

There has been a recent trend of students turning to CCs for educational and professional advancement[4,5,6]. According to the American Association of Community Colleges (AACC), CCs provide a local, affordable, and low-risk path to development and expansion of marketable skills[7]. The trend is especially strong for traditionally underrepresented populations: women, minorities, rural students, veterans, and older Americans[4]. These groups are becoming increasingly central to the United States' mission to graduate more scientists and engineers[8]. However, many of these potential scientists and engineers leave this pathway before completing a four-year degree[9].

Understanding and addressing persistence at the CC level is a multi-faceted task that takes into account fluctuating state funds and a diverse student population[10]. In addition, the enrollment patterns of CC students are complex and may involve multiple transfers across several institutions[11]. However, the academic requirements in engineering that are universal for all CC students can provide a basis for analysis.

Previous research suggests that models based on core-course academic variables are a key aspect in determining retention and graduation in engineering[1,2,3]. In addition, the first year of study in an engineering program has been shown to be critical to success. Levin and Wyckoff[3] developed a freshman-year model that identified the best predictors of retention as grades in Physics I, Calculus I, and Chemistry I.

Most students who leave engineering do so before they have successfully completed these difficult courses[3]. Previous studies have shown that students must acquire proficiency in these key foundational areas to succeed in engineering. For example, in a longitudinal study of over

35,000 pre-engineering students at Purdue, 84% of those who left engineering did so before they completed their pre-professional program[2].

LeBold and Ward[12] also found that the freshman year is critical to retention and that the best predictors of retention were the first- and second-semester grades and cumulative GPA. They found that students' perceptions of their problem-solving abilities in mathematics and science were also indicative of retention. Budny et al.[2] found a strong correlation between first-semester GPA and graduation rates in engineering. Whalen and Shelley[13] also found that the most important variable indicative of retention in STEM fields is grade point average. They found a dramatic increase in six-year retention and graduation rates for as little as a 0.10 increase in GPA for STEM majors. Earlier research by Strenta, Elliot, Adair, Matier, and Scott[14] found that low grades were the most common predictor for all students leaving science and engineering courses.

Pre-college characteristics account for a relatively small but meaningful percentage of variation in retention rates[15]. However, research shows that pre-engineering success measures are weaker predictors of retention in engineering than are grades in core engineering courses[2,3]. Further, the combination of all first-year course grades, measured as end-of-second-semester cumulative grade point average, is a stronger predictor of success than is the grade in any single course.

Multiple data analysis methods have been applied to predict retention and graduation rates by using academic and demographic variables. Conventional predictive models have used logistic regression. Other data analysis methods existing in the literature are summarized by Li, Swaminathan, and Tang[16]:

- Stepwise/Hierarchical Multiple Regression
- Longitudinal Data Analysis
- Covariate Adjustment
- Two-Step Design
- Exploratory Factor Analysis
- Discriminant Analysis
- Classification Tree

A strength of SEM over some other statistical techniques is that it is able to account for and remove the effects of two types or error: measurement error and residual error. Measurement error is created whenever data are gathered by means of a measuring instrument or process that has less than perfect reliability. Residual error is the amount of unexplained variation in the dependent or endogenous variables left after the independent or exogenous variables have accounted for as much variability as possible. Another strength of this SEM model is its ability to incorporate collinear variables yet provide significant effects in the expected direction, after accounting for collinearity present in the model.

Research Questions

What are the strengths of the relationships as determined by a SEM model, between academic variables in core engineering coursework and graduation in engineering for CC transfer students?

How can these findings increase the success of CC transfers to engineering and inform workforce development strategies?

Design/Method

The SEM employed in this analysis was created with Analysis of Moments Structures (AMOS) software combined with SPSS statistical software using academic variables from both the sending and the receiving institutions. The academic variables consist of a student's combined transcript-level data for course requirements in engineering. These include academic data that occur during the first year after transfer through completion of the BP in engineering. The model provides a simultaneous analysis of relationships among the academic variables and provides strength of relationship indicators. The dataset for this study includes 472 in-state CC transfer students who were admitted to the College of Engineering during the fall semesters of the academic years 2002 through 2005. Model worthiness is determined by root mean square error approximation (RMSEA), comparative fit index (CFI), and the ratio of the chi-squared fit statistic to the model degrees of freedom.

In addition to the BP GPA at the sending and receiving institutions, the model uses the number of credits toward BP courses at both institutions as well as the number of credits and GPA for the first fall, first spring, and first year after transfer. These academic variables are hypothesized to correlate with graduation in engineering. The model identifies which academic variables are mediated through the BP GPA at the university and discovers which other academic variables are correlated directly with graduation in engineering. Other non-significant academic and demographic variables were dropped from the model; including the total number of transfer credits, the overall transfer GPA, gender, and the number of learning communities in which a student participated at the University. Note that a student may have transfer credit from other colleges when the institution she or he attended immediately before transfer was an in-state CC, and the number of credits and the GPA in core engineering courses are from the in-state CC only. This may help explain why the overall number of transfer credits and the overall transfer GPA were not significant predictors.

The observed, endogenous variables in the model are:

- Number of BP transfer credits from the sending institution (Tr BP Cr)
- GPA in core-engineering courses from the sending institution (Tr BP GPA)
- Number of first fall credit hours (after transfer) at the receiving institution (first fall Cr)
- First fall GPA at the receiving institution (first fall GPA)
- Number of first spring credit hours at the receiving institution (first spring Cr)
- First spring GPA at the receiving institution (first spring GPA)
- Number of first-year credit hours at the receiving institution (first year Cr)
- First-year GPA at the receiving institution (first year GPA)
- Number of core engineering course credits taken at the receiving institution (BP Cr)
- GPA in core engineering courses taken at the receiving institution (BP GPA)
- Graduation in engineering (EngGrad)

The observed, exogenous variables in the model are:

- ACT Composite score (act cmpst)
- ACT English score (act engl)
- ACT Math score (act math)

Since the data analyzed in this study were collected on in-state community college transfer students in a Midwestern state where nearly all high school students take ACT rather than SAT for college admissions, the vast majority of students in our dataset transferred ACT scores as opposed to SAT scores. Missing data values for variables included in the model were imputed using a Bayesian multiple imputation method incorporated in SPSS. The unobserved, exogenous variables include error terms for each endogenous variable in the model. They represent the residual error that is left after the exogenous variables have accounted for as much of the variability as possible.

Assumptions in the Design

The estimation method used is this model is maximum likelihood (ML). ML assumes that the observations must be independent with multivariate normality for all continuous endogenous variables. This means we treat the 472 CC students in the study as being picked independently and representative of the population of CC transfer students. Although parameter estimates are relatively robust against non-normality, normality checks were performed on all endogenous variables using skewness and kurtosis values. Using a skewness value>|3| and/or kurtosis value >|10| to indicate non-normality[17] all endogenous variables were sufficiently normally distributed to utilize ML estimation (see Table 1).

Table 1 Assessment of normality

Variable	skewness	kurtosis
act cmpst	.144	-.217
act math	.062	-.025
Tr BP GPA	-.212	-.877
first fall GPA	-.491	-.335
Tr BP Cr_	-.203	-1.046
IBP Cr_	.707	-.059
first spring GPA	-.555	-.427
first fall Cr	-1.416	2.308
IBP GPA	-.647	-.144
first spring Cr	-1.021	1.159
EngGrad	.059	-1.996
first year Cr	-.362	1.327
first year GPA	-.461	-.321
act engl	.170	.113

Results

The model, estimated by ML, demonstrates a reasonably good fit with the data (chi square =74.254, *df*=30, $p<0.0001$) and very good index metrics (RMSEA=0.056, Comparative Fit Index=0.991, chi-squared ratio=2.475).

Although the chi-square test for goodness of fit is rejected, this does not undermine the value of the estimated covariance structure of the model, which is consistent with the sample covariance structure of the data. Whether this specific model is actually correct is not known, however, the estimated path coefficients are statistically significant ($p<.05$) and the directions of the relationships are as hypothesized. Prior research about the value of these variables in predicting success in engineering confirms the validity of the relationships estimated by the model.

The model index metrics demonstrate a very good fit. In this model the RMSEA=0.056. According to Brown and Cudeck[18] an RMSEA < 0.08 may indicate a good fit in relation to degrees of freedom and indicate a reasonable error of approximation. For the comparative fit index (CFI=0.991), Bentler[19] suggests that CFI values close to 1 indicate a very good fit. The chi-square ratio (chi square/*df*=2.475) is consistent with the minimum discrepancy that several writers have suggested as a measure of fit. Carmines and McIver[20] suggest that ratios in the range of 2 to 1 or 3 to 1 are indicative of an acceptable fit between the hypothetical model and the sample data.

Figure 1 shows the recursive path model for graduating in engineering (EngGrad). A recursive model means that no variable in the model has an effect on itself. That is, in the path diagram of the model, it is not possible to start at any variable and, by following a path of single-headed arrows, return to the same variable.

Figure 1 shows six variables with significant or very nearly significant positive direct effects on graduation in engineering. They are:

- Number of first spring credit hours ($p=0.055$)
- Number of first fall credit hours ($p<0.001$)
- First fall GPA ($p=0.029$)
- Number of transfer credits toward BP ($p<0.001$)
- First spring GPA ($p<0.001$)
- Overall university BP GPA ($p=0.062$)

Overall university BP GPA is included in the model since it also has a significant mediating effect on graduation. All of the variables correlated with graduation in engineering occur after transfer to the university, with the exception of the number of transfer credits toward BP courses.

Figure 1 also shows four variables with significant positive direct effects on the overall university BP GPA, which becomes a mediating variable for graduation in engineering. They are:

- ACT Math score ($p<0.001$)

- Number of BP credits taken at the university ($p<0.001$)
- First fall GPA ($p=0.003$)
- First spring GPA ($p<0.001$)

This is one of only three times a pre-college variable occurs in the model. The other times are ACT math correlating with the number of transfer BP credits, and the ACT composite score correlating with the transfer BP GPA. As expected, the ACT scores all vary with each other, as shown by the connecting arrows on the model diagram (see Figure 1).

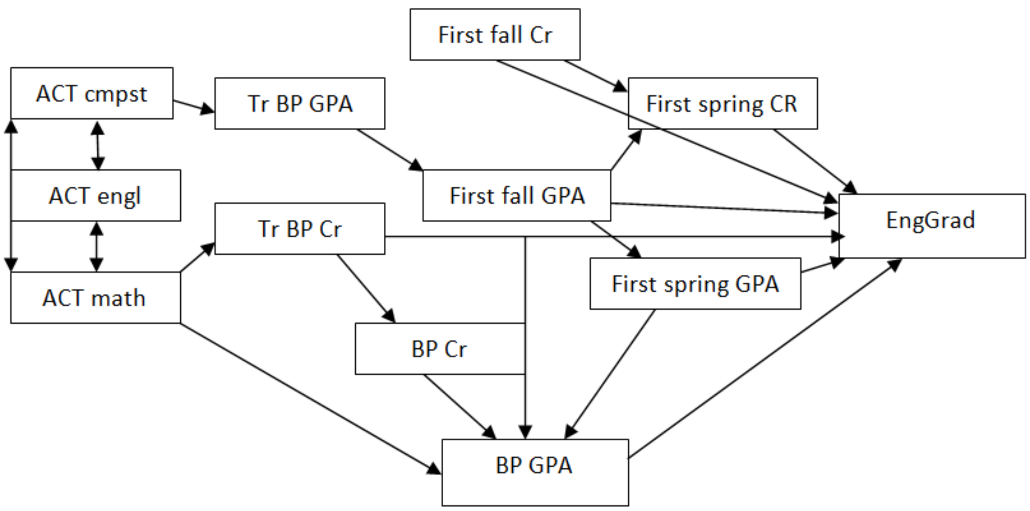

Figure 1 SEM Model

Table 2 gives the regression weights for each statistically significant relationship. These unstandardized estimates are given in terms of the original metric of measurement for each variable. This estimate also can be thought of as the unstandardized effect size. It is followed by the standard error (S.E.), the *p*-value, and the standardized estimate that gives the magnitude and direction of effects measured in unitless standard deviations.

For example, when the ACT mathematics score goes up by 1 point, the BP GPA goes up on average by an estimated 0.044 unit of GPA, holding constant all the other variables in the model. The *p*-value is determined by dividing the parameter estimate by its standard error. The *p*-value means that the regression weight for ACT mathematics in the prediction of BP GPA is significantly different from zero at the 0.001 level (using a two-tailed hypothesis test). The standardized estimate is 0.173, which means that when the ACT mathematics score increases by 1 of its standard deviation units, BP GPA increases by 0.173 of its standard deviation unit.

Table 2 also shows that the variables with the highest unstandardized effect sizes for determining the BP GPA are first spring GPA (0.425) and first fall GPA (0.303). These results measure the estimated increases in BP GPA that correspond with a one-point increase in first fall or first spring GPA, holding all other variables constant. The variable with the highest unstandardized effect size in determining graduation in engineering is the first spring GPA, with estimated unstandardized regression coefficient of 0.115. For a one-point increase in first spring GPA, the engineering graduation rate increases on average by 0.115 percentage points, holding all else constant. The highest overall unstandardized effect size is 0.894, which correlates the transfer BP GPA with the first fall GPA.

Table 2 Regression Weights (Effect Sizes)

Exogenous	Endogenous	Estimate	S.E.	P value	Standardized Estimate
act cmpst	Tr BP GPA	.041	.006	<0.001	.294
Tr BP GPA	first fall GPA	.894	.079	<0.001	.469
act math	Tr BP Cr	.299	.078	<0.001	.170
first fall GPA	first spring GPA	.550	.038	<0.001	.555
Tr BP Cr	BP Cr	-.608	.032	<0.001	-.660
first fall GPA	first spring Cr	.423	.136	0.002	.138
first fall Cr	first spring Cr	.560	.117	<0.001	.555
BP Cr	BP GPA	.021	.006	<0.001	.130
first fall GPA	BP GPA	.303	.101	0.003	.286
first spring GPA	BP GPA	.425	.043	<0.001	.398
act math	BP GPA	.044	.008	<0.001	.173
first spring GPA	EngGrad	.115	.025	<0.001	.242
first spring Cr	EngGrad	.012	.006	0.055	.079
Tr BP Cr_	EngGrad	.013	.003	<0.001	.200
first fall Cr	EngGrad	.030	.006	<0.001	.195
first fall GPA	EngGrad	.060	.027	0.029	.126
BP GPA	EngGrad	.051	.027	0.062	.114

Table 3 gives the squared multiple correlations for each endogenous variable. This measures the proportion of variation for each endogenous variable attributable to its set of exogenous variables. For example, it is estimated that the predictors of BP GPA explain 57.4 percent of its variance, which is the highest amount of explained variance among the endogenous variables. Also, the predictors of graduation in engineering explain 34.8 percent of the variance in that outcome.

Table 3 Squared Multiple Correlations

Variable	Estimate
Tr BP GPA	.087
first fall GPA	.218
Tr BP Cr	.029
BP Cr	.420
first spring GPA	.401
BP GPA	.574
first spring Cr	.138
EngGrad	.348

Table 4 shows the unstandardized total effect (which is a combination of direct and indirect effects) of each row (exogenous) variable on each column (endogenous) variable. For example, the total (direct and indirect) effect of transfer BP GPA on graduation in engineering is 0.139, due to both direct (unmediated) and indirect (mediated) effects of transfer BP GPA on graduation in engineering. The top five unstandardized total effects on graduation in engineering (in terms of percentage point increases) are:

- when Tr BP GPA goes up by 1 unit, EngGrad goes up by 0.139 on average
- when first fall GPA goes up by 1 unit, EngGrad goes up by 0.155 on average
- when first spring GPA goes up by 1 unit, EngGrad goes up by 0.137 on average
- when first fall Cr goes up by 1 unit, EngGrad goes up by 0.037 on average
- when BP GPA goes up by 1 unit, EngGrad goes up by 0.051 on average

Table 4 Unstandardized Total Effects

	BP GPA	EngGrad
act cmpst	0.02	0.006
act math	0.041	0.006
Tr BP GPA	0.479	0.139
first fall GPA	0.536	0.155
Tr BP Cr	-0.013	0.012
BP Cr	0.021	0.001
first spring GPA	0.425	0.137
first fall Cr	0	0.037
BP GPA	0	0.051
first spring Cr	0	0.012

Table 5 shows the standardized total effect of each exogenous variable on the endogenous variables in terms of standard deviation units. This illustrates the portion of the effect that is due to the exogenous variable and the portion of the effect that is due to indirect effects mediated through other variables. For example, the standardized total (direct and indirect) effect of first fall GPA on graduation in engineering is 0.329. The total direct effect of first fall GPA on graduation in engineering is 0.126, which represents 61.7 percent of the total effect.

Modification indices were employed in preliminary models to indicate whether new parameters should be included. The resulting model has no remaining modification indices that exceed the specified threshold in chi-square units.

Table 5 Standardized Total Effects

Exogenous	Endogenous	Total Effect	Direct Effect	Indirect Effect	Indirect % of Total
act cmpst	Tr BP GPA	0.294	0.294	0	0
act cmpst	first fall GPA	0.138	0	0.138	100
act cmpst	first spring GPA	0.077	0	0.077	100
act cmpst	BP GPA	0.070	0	0.070	100
act cmpst	first spring Cr	0.019	0	0.019	100
act cmpst	EngGrad	0.045	0	0.045	100
act math	Tr BP Cr	0.170	0.170	0	0
act math	BP Cr	-0.112	0	-0.112	100
act math	BP GPA	0.159	0.173	-0.014	-8.8
act math	EngGrad	0.052	0	0.052	100
Tr BP GPA	first fall GPA	0.469	0.469	0	0
Tr BP GPA	first spring GPA	0.260	0	0.260	100
Tr BP GPA	BP GPA	0.237	0	0.237	100
Tr BP GPA	first spring Cr	0.065	0	0.065	100
Tr BP GPA	EngGrad	0.154	0	0.154	100
first fall GPA	first spring GPA	0.555	0.555	0	0
first fall GPA	BP GPA	0.506	0.286	0.220	43.5
first fall GPA	first spring Cr	0.138	0.138	0	0
first fall GPA	EngGrad	0.329	0.126	0.203	61.7
Tr BP Cr	BP Cr	-0.660	-0.660	0	0
Tr BP Cr	BP GPA	-0.086	0	-0.086	100
Tr BP Cr	EngGrad	0.191	0.200	-0.009	-4.7
BP Cr	BP GPA	0.130	0.130	0	0
BP Cr	EngGrad	0.015	0	0.015	100
first spring GPA	BP GPA	0.398	0.398	0	0
first spring GPA	EngGrad	0.287	0.242	0.045	15.7
first fall Cr	first spring Cr	0.555	0.555	0	0
first fall Cr	EngGrad	0.239	0.195	0.044	18.4
BP GPA	EngGrad	0.144	0.144	0	0
first spring Cr	EngGrad	0.079	0.079	0	0

Discussion

The objective of this study was to explore SEM statistical models of the academic variables that influence the completion of a BS degree in engineering for CC transfer students. The SEM approach estimates the covariance structure based on hypothesized relationships between the academic variables and the outcome of graduation. Unique in this study is the use of continuous academic variables from both the sending (CC) and the receiving (SU) institution. An understanding of these relationships may promote success for CC transfers to engineering, which in turn may increase the number and diversity of engineers in the workforce[8,9].

The first research question was to determine the strengths of the relationships, as determined by a SEM model, between academic variables in core engineering coursework and graduation in engineering for CC transfer students Two important relationships to academic outcomes were explored: variables that correlated with completion of the core engineering requirements (the BP GPA) and variables that correlated with graduation in engineering including the mediating effect of BP GPA. The predictors with significant positive direct effects on BP GPA were: the ACT mathematics score, the first fall GPA (after transfer), the first spring GPA (after transfer), and the total number of BP credits taken at SU. The variables with the highest effect sizes for determining BP GPA are first spring GPA (0.425) and first fall GPA (0.303).

In addition to BP GPA, the other predictors that had positive direct effects on graduation in engineering were: the number of transfer credits counting toward BP courses, the number of first fall credit hours, first fall GPA, the number of first spring credit hours, and first spring GPA. The variable with the largest effect size in determining graduation in engineering is first spring GPA, with an effect size of 0.115. These findings suggest that reasonable advice to students and their advisors is to focus on coursework that applies to the BP in engineering at the transfer institution. In terms of the unstandardized total effects on graduation in engineering, the following increases in academic variables correspond to increases in the engineering graduation rate and illustrate a possible scenario for the magnitude of increases that have significant effects on graduation rates in engineering:

- when Tr BP GPA goes up by 1 unit, EngGrad goes up by 0.139 on average
- when first fall GPA goes up by 1 unit, EngGrad goes up by 0.155 on average
- when first spring GPA goes up by 1 unit, EngGrad goes up by 0.137 on average
- when first fall Cr goes up by 1 unit, EngGrad goes up by 0.037 on average
- when BP GPA goes up by 1 unit, EngGrad goes up by 0.051 on average

The results of this study emphasize the importance of early success in core courses (the BP in engineering) for attainment of an engineering degree. These findings reinforce the results of previous research conducted by Whalen and Shelley,[13] who found that the most important predictor of retention in STEM fields is grade point average. They found a dramatic increase in six-year retention and graduation rates for as little as a 0.10 increase in GPA for STEM majors. Schools have found that success strategies such as tutoring, supplemental instruction, and counseling are effective in helping students complete these high-risk courses with better grades[2]. After controlling for student's pre-entry characteristics, Shelley and Hensen[21] found that supplemental instruction participants in engineering mathematics and physics courses earned significantly higher percentages of A and B grades, significantly lower percentages of D and F grades and withdrawals, and significantly higher mean final course grades than did non-SI participants.

Collaborative learning strategies are a well-documented way to increase grades in difficult courses[22, 23]. Many men and women who form study groups report that they both enjoy their work more and feel they learn more because of the academic discussions in these groups. "Collaborative learning strategies solve two of the most vexing pedagogical programs: large class sizes and gross differences in education preparation."[24]

Placement in pre-calculus has validity in increasing success rates. Purdue University found that students placed in pre-calculus who successfully mastered the material (defined by earning an A in the course) were enabled to have similar retention rates as those with mathematics SAT score advantages of up to one hundred points[2].

Academic variables occurring after transfer generally correlate higher with graduating in engineering than do the pre-collegiate or other transfer variables employed in this study. This finding emphasizes the need for transfer students to be prepared for the academic rigor after transfer. Enrollment partnership programs have been shown to create a smoother transfer process, which in turn may lead to improved grades[25]. The National Academy of Sciences recently published a report indicating that students often begin their two- or four-year study with too little preparation. Preparation in mathematics, reasoning, and critical thinking are necessary for students to succeed in STEM careers[26]. This will aid students with early success in variables shown to correlate with graduation in engineering

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