Modeling Freshman Engineering Success

by

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***ENGINEERING* STUDENT SUCCESS**

Dedication

To all future College of Engineering Freshmen

Acknowledgments

I would like to thank my research committee for their dedication in showing me successful practices in research. In particular, I would like to thank my advisor, Professor Gary D. Herrin, for his continuous and energetic guidance in completing this research, and our many discussions on engineering student success. I would also like to thank Professor Eric L. Dey, for our many discussions about education research and factor analysis and his continuous support. I would like to thank Dr. Cynthia Finelli for her support and knowledge about engineering education and Professor Lawrence M. Seiford for his guidance in pursuing a Ph.D.

I would especially like to acknowledge the contributions of Dr. Malinda Matney for her long-term planning with the CIRP survey at the University of Michigan. With this planning, I have been able to conduct an empirical analysis that is far more complete and analytical than otherwise. Dr. Matney and Andrew Cameron provided the database support for the initial research database. I would also like to thank the College of Engineering staff for their support and Darryl Koch, for providing the College of Engineering data for this research effort. I would like to thank Ms. Gillian M. Nicholls of the University of Pittsburgh for sharing her research on STEM categories with me.

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Finally, I would especially like to thank my husband, Douglas, for his conversations on engineering, his continuous encouragement, and arranging his schedule to fit my student schedule.

A paper titled "Is the Modeling of Freshman Engineering Success Different from Modeling of Non-Engineering Success?" based on the research discussed in Chapter VII has been accepted for publication in the *Journal of Engineering Education* in 2008.

Foreword

After a career as a quality and reliability engineer at some of the best engineering companies in the U.S., I was motivated to come back to Michigan to pursue a Ph.D. I felt that the ideas of process improvement, which have been successfully applied in engineering companies, could be applied to improving the teaching and learning processes for high school and college students. I was looking for a broader education that would give me the knowledge and understanding to research and improve the interface between high school and engineering education.

When I started in the PhD program, I read *The Engineer of 2020,* a book developed by the National Academy of Engineering's Committee on Engineering Education. This landmark book discussed the need for more engineers, the need for change in engineering colleges and the need for engineers to solve social problems. I pursued the idea of modeling freshman engineering retention as my PhD research topic. Much of Industrial Engineering is about systems modeling and I used the research tools of Industrial Engineering to model freshman engineering retention. My favorite phase became "engineering student success".

There is much discussion about women engineering students not believing that an engineering career is for them. A career decision must be made on an individual basis. I would like to go on record as a Michigan Engineering alumna that I truly enjoyed my career as a Michigan engineer and found it very rewarding.

I plan to continue the journey in improving the educational processes that help engineering students be successful. Much more effort is needed in the area of engineering education research. I hope you enjoy reading my dissertation. Most of the significant results are in Chapters V and VI for engineering student success at Michigan. Enjoy!

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LIST OF ABBREVIATIONS

CIRP	Cooperative Institutional Research Program
EAC	Engineering Advising Center
Engin, Engr	Engineering
GPA	Grade Point Average
HERI	Higher Education Research Institute at UCLA
IRB	Institutional Review Board
STEM	Science, Technology, Engineering and Mathematics
STEM GPA	Grade Point Average of all freshman level STEM courses
URM	Under-Represented Minority Includes Blacks, Hispanics and Native Americans

ABSTRACT

The objective of this research was to model freshman engineering success, using education theory and statistical modeling techniques. Freshman academic success and retention were modeled from pre-college characteristics. The UCLA/CIRP survey was used in this to survey students' pre-college attitudes and experiences. An empirical analysis was conducted at the University of Michigan to validate the model using factor and regression analysis.

Three research objectives were explored:

- Define a proposed model based on the significant pre-college predictors of engineering student academic success and retention from the literature and determine if the empirical data support the proposed model.
- Define and explore the effectiveness of selected intervention strategies for student academic success and retention.
- Evaluate if the predictors of student success and retention are different for engineering students than for non-engineering students. Three student sectors other than engineering were considered: pre-med students; students pursuing an intended major in science, math or a technical field; and students with an intended major in the social sciences, humanities or business field.

The significance of this research is that it proposed and validated a model for engineering student success. Prediction equations for both academic success and retention were developed. The modeling of freshman student success of the Engineering discipline was compared to the Pre-Med, STEM and Non-STEM disciplines. The only factor that was a common predictor for academic success for all four disciplines was the factor that included the high school GPA and class rank. All other significant predictors were

discipline specific. This finding supports that the modeling of freshman engineering student success is different from the modeling of general college freshman success. Significant predictors unique to freshman engineering academic success (GPA) included the factors related to quantitative skills preparation (ACT Math and Science test scores and the math and chemistry placement tests) and confidence in quantitative skills (self-rating of math and computer abilities). Significant predictors for freshman engineering retention were high school rank and concern about financing a college education.

CHAPTER I
INTRODUCTION

1.1 Motivation

The U.S. engineering community is concerned with the predicted shortage of engineers in the workplace (NAE, 2004; NAS, 2005). Data from the U.S. Bureau of Labor Statistics indicates that 43% of the growth in new jobs will be in engineering and computer related careers from 2004 to 2014; this equates to an average 4% growth in engineering jobs per year (Hacker, 2005; cited in US Department of Education, 2006). At the same time, a large number of scientists and engineers are reaching retirement age, increasing the total growth in engineering jobs to 6% per year (based on statistics from the National Science Board (NSB), 2006). Yet, the number of students enrolled in engineering bachelor programs has remained constant from the mid-1980s to 2003 (NSB, 2006). Looking further back in the pipeline to students in high school, there is less interest in an engineering career among high school students. ACT reports that the percent of high school students who took the ACT test and indicated an interest in an engineering major has declined by 36% from 7.6% in 1995 to 4.9% in 2005 (ACT, 2006). If these trends continue, it is expected that the U.S. will have a significant shortage in engineers.

In addition, a major concern is the effect of a shortage of engineering on the innovative competitiveness of the U.S. With a shortage of Bachelor engineers, the pipeline for research engineers is decreased; this can have a significant effect on the innovation competitiveness of the U.S. (NAS, 2005). Related to the issue of innovative competitiveness, the U.S. is falling behind other countries in the production of scientists and engineers. In China, 60% of all Bachelors degrees are earned in science and engineering. This compares to 30% of all Bachelor degrees are earned in science and engineering in the U.S., of which only 5% are engineering (Friedman, 2006, 331; NSB, 2006). With a shortage of engineers in the U.S., the innovation competitiveness issue is expected to become a more serious problem.

There is hope that women and minority engineers will help make up the deficit in number of new engineers. Women constitute 56% of the U.S. population, but women earn only 20% of the Bachelor engineering degrees (Grose, 2006). Likewise, minorities constitute 30% of the college age population (NSB, 2004) and, by 2020, are expected to constitute 37% of the U.S. population (National Center for Public Policy and Higher Education, 2005). In 2001, NSF reported that minorities earned only 13% of the Bachelor degrees in engineering. This data suggests that minorities and women must be more strongly recruited into the engineering programs, in order to meet the projected growth in engineering jobs.

As an overall indication of this national crisis, the National Science Board has recently expressed their concern. They have recommended that "the Federal Government must direct substantial new support to students and institutions in order to improve success in S & E [science and engineering] study by American undergraduates from all demographic groups" (NSB, 2007).

In the larger picture of the challenges that universities are facing today, student retention is one factor that a university considers in measuring its effectiveness in serving its students, faculty and staff. To achieve better effectiveness, more emphasis is being placed on continuous improvement. Dew recently wrote, "What's new in higher education is the increased emphasis on continuous improvement and the growing appreciation of quality management systems" (Dew, 2007). Within the framework of continuous improvement, student success is a significant part of the effectiveness effort by universities, and continuous improvement in retention rates will continue to be emphasized.

Given the overwhelming data that supports a shortage of engineers in the next ten years, a short-term solution is to increase the graduation rates of engineering colleges. The average graduation rate of all U.S. engineering colleges is under 55% (Clough, 2006). A 10 to 20% improvement in this average graduation rate would substantially increase the number of new engineers to the engineering workforce and research community, and improve the institutional effectiveness of the university. A component of the graduation rate to consider is the freshman retention rate, which represents the percent of students who stay in an engineering program after their freshman year. Research supports that the freshman year tends to have the lowest retention of all the college years (Tinto, 1993). Figure 1-1 shows the relationship between the six-year graduation rate and the first year retention for research universities, which have very large research efforts (categorized by the Carnegie classification of Research University-very high research activity)[1] (Education Trust, 2007). These universities tend to have the higher graduation rate compared to all colleges and universities. Note the large variation in the graduation rates for these universities.

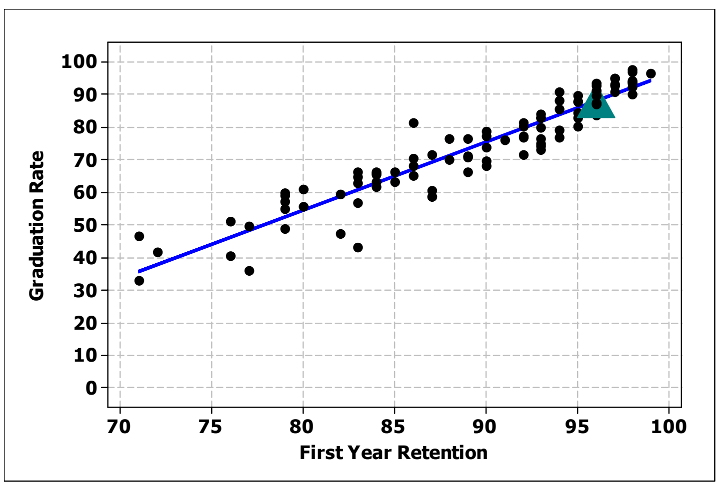

Figure 1-1: The Higher the First Year Retention, the Higher the Graduation Rate

[1] Figure 1-1 was generated from the College Online Results Database at the Education Trust website: http://www.collegeresults.org/ The Carnegie Classification of Research University-very high research activity is defined as "at least 20 doctorates …and scored very high on either or both an aggregate and/or a per-capita index measuring research and development (R&D) expenditures in science and engineering (S&E), R&D expenditures in non-S&E fields, S&E research staff, and doctoral conferrals in humanities, social sciences, STEM, and other fields."

The University of Michigan is represented as the blue triangle on this graph.

1.2 Modeling Freshman Success

Modeling of retention rates can help identify key variables that affect the graduation rate. Since the freshman year typically has the lowest retention rate of all years of engineering college, the most benefit to increasing the graduation rate is to model the freshman engineering retention. Based on this modeling, the development of related interventions that help students succeed could lead to a higher freshman retention rate. As shown in Figure 1-1, a freshman retention rate is highly correlated with a six-year graduation rate.

In modeling retention rates, one of the considerations is whether to use data from a multi-institutional study or a singe-institution study. The first major studies of engineering retention were multi-institutional studies, including the Astins study and the Adelman study (Astin and Astin, 1992; Adelman, 1998). These studies showed general national trends and significant patterns that explained significant predictors of engineering student success and retention including high school academic preparation, the intensity of the high school curriculum, math and science preparation, aspiring to a career in engineering, and having a strong orientation towards science. The Astin and Astin study was based on a survey of pre-college characteristics, including high school attitudes and experiences and expectations for the college experience. The strength of a multi-institutional study is that it presents a consistent set of inputs from all universities. The same admission tests (ACT/SAT) or the same surveys can be collected and prediction trends across many universities can be defined. The weakness of a multi-institutional study is that it is difficult to study interactions between variables. In addition, it is very difficult to study intervention support activities because they will vary from institution to institution.

On the other hand, with single-institution studies, it is easier to model relationships between variables and their interactions, and understand the effect of a particular intervention on student academic success and retention. Student retention is the intersection of an educational institution's efforts to support students and the student's decision to stay. The institution defines the climate, the curriculum, the advising center and numerous other activities that help the student both academically and socially. Ultimately, the student decides to stay or leave. This decision is based on a number of factors. A single institution study allows the study of this decision in more detail. In fact, some researchers have suggested that more single-institution studies on student success and retention are needed (Braxton, 2000; Dey, 2007). Single institution studies allow an analysis of which intervention strategies are most effective, taking into account the high school preparation levels of the students. Especially for public universities, it is necessary to effectively use the available student support dollars, which are usually substantially less than at private universities (Veenstra and Herrin, 2006b).

1.3 The University of Michigan Selected as a Single-Institution Study

Because of the advantages of a single institution study, it was the preferred study for freshman engineering retention. One of the considerations in modeling freshman engineering retention was to select the University of Michigan as the institution to study. The University of Michigan was considered for the following reasons:

1. **The University of Michigan Has a High Percent of Students who Stay and Graduate in Engineering**

   If we are to understand freshman success and retention, we need to study universities that are successful at retaining students. Tinto has observed, "Leaving is not the mirror image of staying. Knowing why students leave does not tell us, at least directly, why students persist. More importantly, it does not tell institutions, at least not directly, what they can do to help students stay and succeed (Tinto, 2006). Therefore, research success requires the study of engineering student retention at successful universities. The University of Michigan has one of the highest freshman retention rates and graduation rates both at the university level at the College of Engineering level. At the university level, the first year university retention averages 96% and the six-year graduation rate averages 85% (University of Michigan, 2006). In Figure 1-1, the University of Michigan is shown as the triangle point. In Michigan's College of Engineering, 75% of the entering freshmen graduate with Bachelors in engineering and 85% graduate with Bachelors in engineering or another major (University of Michigan, 2007a). The 75% graduation rate equates to a 36% increase over the average of all engineering colleges (i.e. 55%). Similar to the national statistics, the experience at Michigan is that the freshman year has the lowest retention for engineering students. However, with a freshman engineering retention rate of 94% (retained in the College of Engineering based on this project's data), Michigan has one of the highest freshman engineering retention rates. (National statistics on the freshman engineering retention rate are not publicly available.) If we want to understand why students stay, we need to model universities like the University of Michigan with established high retention rates.

2. **Adds to the Body of Knowledge about Freshman Engineering Retention**

   Because 78% of the engineering students graduate from large research universities (NSB, 2004), an engineering student success study at a large research university adds substantially to the body of knowledge about engineering student success and retention. There are very few freshman engineering retention studies from large research universities, whose engineering college ranks in the top 10. A University of Michigan freshman engineering student success modeling study of this magnitude has not been conducted, and published in the research literature.

3. **Answering the Question of How Engineering Success is Different**

   In addition, a single institution study of Michigan is ideal because it allows the study and modeling of student academic success and retention of engineering students compared to other student groups. This is particularly significant because Michigan is a larger research university with diverse educational goals and programs. In particular, in this research, an engineering model was developed and used to compare the student academic success (first year GPA) and retention of engineering students with pre-medicine majors; science, math and technology majors; and social studies, humanities and business majors.

In order to study freshman engineering academic success and retention and select appropriate variables, an educational model was needed. As part of this research, a literature-based model using both the engineering education and education literature was developed.

1.4 Research Objectives

In summary, the research objectives are three-fold:

1. Develop a literature-based model for freshman engineering academic success and retention, based on pre-college characteristics and validate this model with an empirical study using University of Michigan student data. Significant pre-college characteristics that predict both academic success and retention will be examined. A second cohort will be used to cross-validate the model.
2. Determine the effectiveness of current engineering intervention strategies, when the significant pre-college characteristics are taken into account. These interventions included advising and an engineering career survey course. Since this is a single-institution study, the interventions can be studied more easily and within the context of the model.
3. Determine if the modeling for the engineering sector is different from the modeling of non-engineering sectors. Are the predictors of student success and retention different for engineering students than for non-engineering students? Three non-engineering student sectors were considered: students intending on a career as a physician; students pursuing an intended major in science, math or a technical field; and students with an intended major in the social sciences, humanities or business field.

These research objectives support the underlying thesis that the modeling of freshman engineering retention is different from general college retention and that freshman engineering success can be substantially improved. The discussion on the model and empirical studies follows.

Overview of the Model for Freshman Engineering Success

In modeling freshman-engineering success, Tinto's model (Tinto, 1993) was selected and revised, for the development of a literature-based model of freshman engineering retention. The model for student success is illustrated in Figure 1-2 as two models: the first for academic success and the second for student retention. Two models are needed because the modeling techniques are different for each model. Because the freshman year is a transition year from high school to engineering college, the inputs to the student success model were pre-college characteristics. Pre-college characteristics, including overall academic preparation and quantitative skills, were shown to be significant in the Astin and Astin (1992) and Adelman (1998) studies. Also significant were attitudes and career goals (significant in the Besterfield-Sacre, et al. (1997) study, and high school activities. These were considered as important predictors of academic success (in terms of the first year GPA) and retention.

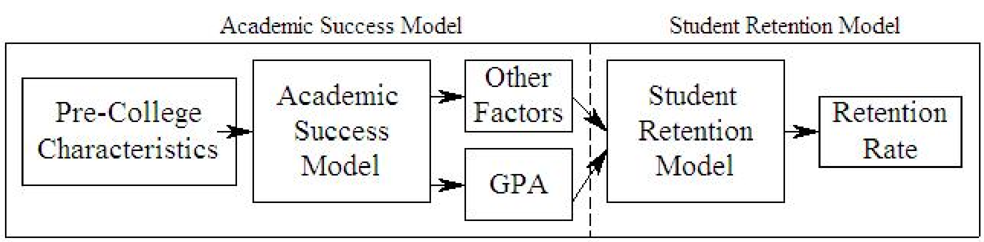

Figure 1-2: Student Success Model

The outputs from the academic success model include two measures of student academic success

- Overall academic success - First year GPA

- Academic success for the STEM courses - First year GPA of the science, technology, engineering and math (STEM) courses

In addition, the outputs from the student retention model include two measures of student retention:

- College retention (returning to engineering at the beginning of the 2nd year)
- University retention (returning to the university at the beginning of the 2nd year).

Modeling Techniques include Regression Modeling

The success of statistical modeling is dependent on both the method of modeling and the data used in the modeling. Consistent with Figure 1-2, two models were developed and validated:

1) A model with the first year GPA as the dependent variable, and the pre-college characteristics as the independent variables.
2) A model with a dichotomous variable of staying in engineering or leaving engineering as the dependent variable and the first year GPA and selected model variables as the independent variables.

In the first model, modeling of the college GPA is usually achieved using a form of regression analysis (Besterfield-Sacre et al., 1997; Levin and Wyckoff, 1988) but has been approached with a structural model (Platt, 1988, French et al., 2003). Regression analysis was preferred over the structural model because of the need to eventually test a hypothesis of differences in gender and ethnicity, controlling for the significant pre-college characteristics. It is common in both engineering and education research to use a principal component analysis or factor analysis to define the underlying correlation structure of the independent variables. In this case, the principal axis factoring method was used to define the common correlation structure. From this analysis, the defined factors were entered into the regression analysis. Two freshman cohorts were actively used; the 2004 freshman class cohort to estimate the coefficients of the regression model, the 2005 freshman class cohort to validate the prediction accuracy of the model.

In the second model, several approaches have been taken in the past. The first, as was conducted by Elkins and Leutkemeyer (1974), was that of identifying the "persisters" and "leavers" and using an F- test to test for a significant difference in the averages of the two groups. It is descriptive, but does not lead to a statistical model for retention. The second approach is to use logistic regression or ordinary regression as a substitute for logistic regression. The third approach is to use a structural model. This approach can have some difficulties in defining the paths correctly. Due to my experience with logistic regression analysis, I chose to use logistic regression, which is the most common approach in modeling freshman engineering retention. The logistic regression has been used very successfully by engineering education researchers (Astin and Astin, 1992; Levin and Wyckoff, 1988; Besterfield-Sacre et al., 1997; Scalise et al., 2000, French et al., 2005). A dichotomous variable usually was defined based on whether or not a student returned to engineering and the independent variables were the model predictors of interest. Astin and Astin (1992) used a dichotomous variable to define whether a student was an engineering major or not.

Choice of Survey for Pre-College Characteristics

A survey was needed to include variables related to pre-college characteristics such as motivation and career decisions for each student in the study. There were three options: an independent survey, the PFEAS© survey or the Cooperative Institutional Research Program (CIRP) survey.

An independent survey would need to be developed and validated. It would have the advantage that specific questions related to the University of Michigan engineering program could be asked. It had the disadvantage that it would need to be an online survey, which typically generated a low response rate. It would take more time to validate the survey. In addition, due to the need to administer the survey at the beginning of the freshman year and wait one year to collect data on the freshman retention status of each student, only one year of data would be available.

The Pittsburgh Freshman Attitudes Survey (PFEAS)© was developed at the University of Pittsburgh and had the advantage of surveying students specifically about their attitudes about an engineering career, confidence in engineering skills and how much they liked math and science (Besterfield-Sacre et al., 1997). To implement it would have required an online survey and would have been limited to one year.

The UCLA's Cooperative Institutional Research Program (CIRP) survey was already available for three freshmen years; this was a major advantage. The CIRP is a 40 year old program of research currently operated by the UCLA Higher Education Research Institute (HERI). It has been administered throughout the U.S. annually to first-time, full-time college freshmen to measure their beliefs, goals and characteristics and is a recognized survey for retention studies. The 2005, the CIRP survey was administered to over 263,000 students at 385 colleges and universities (Pryor, et al., 2005). Its disadvantage was that it did not ask as many questions about attitudes towards engineering as the PFEAS©. Yet, the CIRP surveys have a number of questions on major, career, motivation and goals.

The decision was made to use the CIRP survey; data from the survey was then combined with student performance data and engineering intervention data. Based on the model's pillars of student success, approximately sixty variables were selected to be included in the empirical analysis and validation of the model.

Study of Gender and Ethnicity Differences

Because of the concern over increasing the number of women and minority engineers, it is important to ask whether women and minority engineering students are as academically successful and retained at the same rate as majority men students. Statistical hypothesis testing was conducted with a generalized linear model technique to test for statistical differences in gender and ethnicity within the context of the model.

Study of Interventions and Course Placement

Engineering education researchers have shown early intervention to be important for engineering student success. A key paper on early intervention was that of Budny et al. It showed that correct placement into the first term courses was key for engineering retention (Budny et al., 1998). Besterfield, et. al. (1997) showed that student attitudes towards engineering can influence retention in engineering. The basic question is what practices are effective in helping students with academic achievement. Two interventions for student success and retention were studied in the context of the developed model:

- Advising
- Survey course in engineering careers, Engineering 110

In this analysis, a randomized database technique was used to reduce bias due to common participation in several intervention programs by students. In addition, an independent study of mentoring is also reviewed. Because of the importance of correct placement into the first term courses (Budny, 1998), an approach to course placement was proposed and applied in this research.

Based on this analysis, recommendations for improving retention will be discussed.

Comparison of Engineering to other Student Sectors

Using the predictors from the model, predictors of academic success and retention were compared between engineering students and three other student sectors: students intending on a career as a physician,; students pursuing an intended major in science, math or a technical field; and students with an intended major in the social sciences, humanities or business field. This will define how modeling of engineering student success is different or the same as these three other student sectors at the University of Michigan. As a single-institution study, a more consistent comparison can be conducted since the admissions process is common and the underlying culture for student success is the same.

Comparison of ACT and SAT scores as Predictors

Although almost all engineering retention studies tend to use the SAT Math, my previous research showed that the ACT Math is a better predictor of success in Calculus and Chemistry than the SAT Math test (Veenstra and Herrin, 2006a). Most engineering education retention studies use the SAT Math test score as a predictor . The State of Michigan is replacing the Michigan Educational Assessment Program (MEAP) at the high school level with the Michigan Merit Exam, which is the ACT test and the state covers the cost of testing. (Michigan Department of Education, 2007). More Michigan residents, who apply to the University of Michigan, will therefore report the ACT test. This increases the need to understand the effectiveness of the ACT test scores as predictors of student success. Therefore, the research plan proposed two subsets: a subset that included students who reported their ACT results and a subset that included students who reported their SAT results. The models developed from each subset were compared for predictiveness.

1.5 Student Success in the Context of Quality Improvement Theory

With my background, I approached the development of a model of freshman engineering success from a quality engineering and improvement perspective. During the past five years in which I have worked on my PhD, the paradigms on student success have changed in higher education and engineering colleges. For this reason, I decided to include this section in the Introduction. This section discusses some of the past and current trends related to quality improvement theory and it provides a backdrop for this thesis on engineering student success.

To begin with, I would like to address the impact quality improvement thinking is having on university operations. Dew reports, "The use of quality principles and methodologies is becoming more popular, and they are being adopted all levels of higher education throughout the country… higher education is seeing an upswing in interest in --and the application of – quality management" (Dew, 2007). Dew goes on to report,

> "Higher education has always held a strong interest in quality assurance. For decades, regional accreditation ….have focused on ensuring the quality

> of academic programs, qualifications of faculty, adequacy of library resources, adherence to admission standards and academic independence of colleges and universities. What's new in higher education is the increased emphasis on continuous improvement and the growing appreciation of quality management systems" (Dew, 2007).

How has this increased emphasis on continuous improvement come about and what impact does it have on a theory of engineering student retention? A brief history of quality improvement theory is needed to explain this and identify concepts that are relevant to a model of engineering student success.

Most knowledge of quality management and continuous improvement in quality can be traced back to the thinking of Walter Shewhart. In the 1930's, he observed that quality represented the "goodness of an object" and defined quality of a product as the value of a characteristic, such as length or velocity (Shewhart, 1931). By the 1950's, the focus of quality engineering theory was on producing parts that were within engineering specifications and the theory of statistical process control was well established. In the "quality decades" of the 1970's, 1980's and 1990's, statisticians W. Edwards Deming, A.V. Fiegenbaurn and Joseph Juran, were expanding the definition of quality to include customer satisfaction and value added. Deming developed 14 points of quality management for business, including being customer focused and having a 'profound knowledge" of a process. Deming also took Shewhart's Plan-Do-Check-Act (PDCA) cycle of scientific thinking and re-emphasized this feedback kind of thinking about processes (Deming, 1994).

As quality management and continuous improvement strategies have developed, the ideas of quality and continuous improvement were expanded in manufacturing to include Total Quality Management, a quality management approach for business, Six Sigma and the ISO9000 quality standards. Six Sigma was originally developed at Motorola as a continuous improvement approach to reducing manufacturing variability (Godfrey, 2002). Motorola's emphasis on an aggressive continuous improvement process to reduce variability, improve customer satisfaction and increase innovation in design and processes was driven by global competition. Six sigma programs use design of experiments, statistical process control and other quality tools in an integrated approach. In the 1980’s, the criteria of the Malcolm Baldrige National Quality Award (MBNQA) evolved out of the concepts developed by Drs. Deming, Juran and Fiegenbaum and the six sigma programs. Motorola was the first company to win the MBNQA. Central to both MBNQA and Six Sigma are goal-oriented, customer focused and data-driven paradigms. The MBNQA provides a systematic framework for organizational excellence and continuous improvement (National Institute of Standards and Technology, 2007).

These ideas of quality improvement moved from manufacturing to the service industries. When MBNQA was modified for educational institutions in the mid-1990s, MBNQA found more acceptance among educators. A broader definition of quality that blends continuous improvement in quality into strategic planning and institutional effectiveness began to emerge. The MBNQA in Education included constructs of learning-centered education, valuing of faculty and staff, focus on results and visionary leadership. In 2001, the University of Wisconsin-Stout became the first university to win the MBNQA (Cokeley, 2006)... Prior to 1999, most accreditations on colleges were based on the reputation (quality) of the faculty, the number of courses in a particular discipline and the number of volumes in the library and the accreditation process included auditing a college’s quality once every five or seven years. In 1999, the North Central Accreditation of Colleges and Schools implemented an alternative accreditation, Academic Quality Improvement Program (AQIP) that focuses on active continuous improvement projects of both academic and administrative processes on an annual basis (AQIP, 2007). At about the same time, the ABET accreditation process for engineering colleges was revised focusing on continuous improvement and student learning outcomes. (ABET, 2007)

The University of Michigan has a strong history of participating in quality improvement transformations since the mid-1990’s (Dew and Nearing, 2004). This transformation at Michigan began at the President’s level, with a series of presidential commissions on key issues, with communication about the transformation in the entire university community (Duderstadt, 2007).

With the National Academy of Sciences' report, *Rising above the Gathering Storm: Energizing and Employing America for a Brighter Economic Future*, there became a national focus on the need for more engineers, better-prepared students entering engineering colleges and a higher graduation rate of engineers from engineering colleges (NAS, 2005). Motorola invented Six Sigma because of global competition, the need to be more innovative and more customer-focused; likewise, U.S. engineering colleges are being pressured by global competition for engineering know-how and innovation to produce more engineers (i.e. improve their graduation rates)

At many universities, quality improvement is embedded in institutional effectiveness programs. With less funding from states, universities are striving for quality improvement in student success with smaller budgets. The ideas of quality improvement are becoming more relevant to universities. In fact, in the final report of the Secretary of Education's Commission on the Future of Higher Education entitled *A Test of Leadership: Charting the Future of U.S. Higher Education,* the commission recommended: "We recommend that America's colleges and universities embrace a culture of continuous innovation and quality improvement." (U.S. Department of Education, 2006)

Consider freshman retention (percent of students who return for the second year). More universities are addressing freshman retention from a quality management approach. They want to know what processes lead to a high retention rate. The tradeoffs in institutional effectiveness are the cost of losing students (three years tuition) versus the cost of programs that help students be successful, such as tutoring and mentoring programs. As a result, the idea of a quality education is emerging to include a value-added education that is also student-focused. In the development of an engineering student success model, these concepts of quality improvement and institutional effectiveness become important to the underlying paradigm of thinking about student success.

1.5 Outline of the Thesis

In this thesis, the research questions ask how the freshman engineering student academic success and retention are different from general college student academic success and retention at the University of Michigan. This research question is answered within the framework of the development of a new model for freshman engineering retention. Chapter II includes a literature review and development of a literature-based student success model for freshman engineering success. In preparation for the validation of the model, Chapter III documents the variable development and data management related to this project. Chapter IV explains and evaluates the factor analysis. Chapter V discusses student academic success for engineering students and analyzes the effectiveness of the engineering intervention support activities within the context of the model. It also proposed a new approach to course placement. Chapter VI discusses the retention of engineering students and includes a sensitivity analysis of retention. Chapter VII continues the development of the thesis that freshmen engineering retention is different from general college retention with the comparison of student success of engineering majors to pre-med students; science, math and technology majors; and social science, humanities and business majors. Finally, Chapter VIII makes recommendations for improving freshman engineering student academic success and retention based on this research.

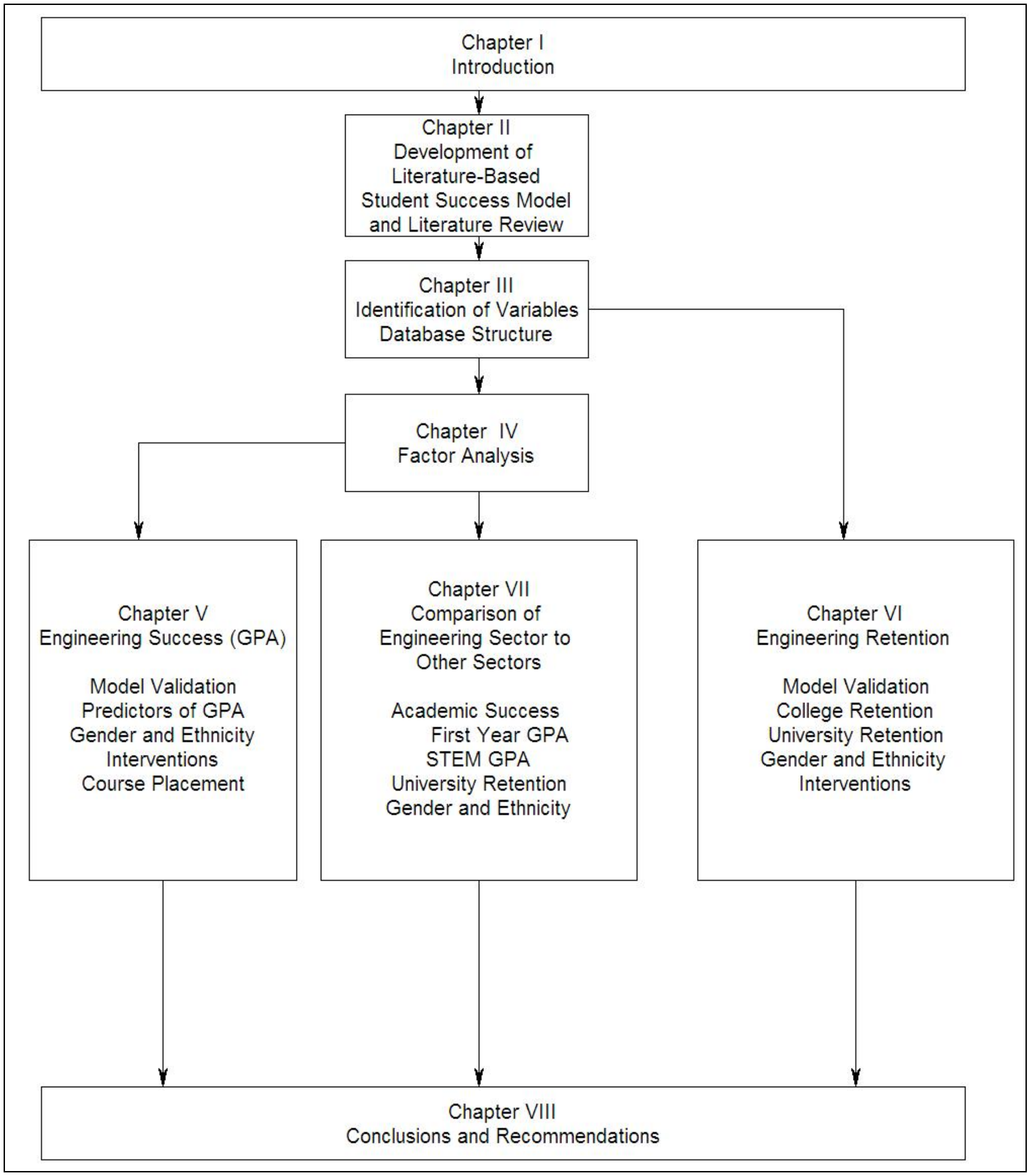

Figure 1-3 Chapter Development of Dissertation

CHAPTER II
LITERATURE REVIEW AND DEVELOPMENT OF A MODEL FOR ENGINEERING STUDENT SUCCESS

The engineering education literature has a growing body of empirical studies on freshman engineering student success and retention. This chapter both develops a new model for freshman engineering success based on engineering education and education research literature and reviews the literature upon which the model was based.

Student success was defined in terms of both academic success and retention. Academic success was defined in terms of first year GPA. Previous researchers have discussed student academic success in terms of the GPA. (Levin and Wyckoff, 1988; Lackey et al., 2003; French, et al., 2005). Retention of a student was defined as the student returning for academic studies in the second year. Retention can be considered within either the engineering college or the university. Different techniques are used for predicting academic success and student retention. As a result, the overall student success model was viewed as two adjoining models (Figure 2-1).

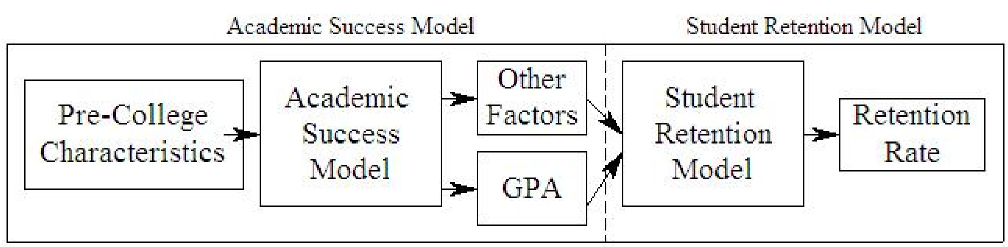

Figure 2-1: Student Success Model

Students have various experiences, both academic and social, in high school. They bring these experiences to college with them. The transition from high school to college is a major life style transition. It is a reasonable assumption that the pre-college characteristics that define these experiences are major contributors to both academic success in the freshman year and the decision the student and his/her family make at the end of the freshman year of whether to return to engineering college for the second year. My thesis is that freshman engineering retention is different from (general) college retention. For this reason, I wanted to develop a model on freshman engineering retention based on the pre-college characteristics. Figure 2-1 shows this emphasis with pre-college characteristics as input to the academic success model.

In the development of the overall student success model, the following will be discussed:

- The importance of a model relative to empirical studies (Section 2.1)
- Previous models of engineering retention (Section 2.2)
- Education theories and Tinto's model for attrition (Section 2.3)
- A new model of freshman engineering retention (Section 2.4)

The literature review of the dissertation will be integrated into the development of the model.

2.1 Importance of a Theory

In developing a model or theory of student success, it is important to understand the importance of a model. The word model is often interchanged with the word theory. My preference is to use the word model to describe my "model" of engineering student success, but some researchers prefer to use the word theory. Tribus described a theory as a "connected set of concepts" and explained that the concepts that make up the theory are needed to predict the future based on actions that are taken (Tribus, n.d.). Deming wrote, "Without theory, experience has no meaning" (Deming, 1994, p. 103). Deming understood that "profound knowledge" required a theory. "Profound knowledge" was Deming's terminology for completely understanding a process. Peter Senge indicated the need for mental models or theories in order to lead and to understand what can be accomplished (Dean, 2004).

Clearly, a theory was needed to understand and further develop an understanding of engineering student success. A model provides a standard by which to judge empirical studies and then revise the model into a better model. Box, Hunter and Hunter (1978) discuss this process of model development in terms of deductive and inductive thinking for scientific research about a process. A model is developed; a deductive thinking process is used to compare the data to the model; based on the data, an inductive thinking process is used to change the model if the data does not agree with the model. In this sense, the model may be viewed as a hypothesis. The empirical analysis is validation of the hypothesis. If the empirical analysis does not validate the model, the model may need to be changed. This iterative process eventually determines the validity of the model. In the context of the Shewhart Plan-Do-Check-Act cycle, the model is the "plan" stage, the empirical study is the "Do" stage, the validation of the empirical results to the model is the "Check" stage and modifications to the model is the "Act" stage. An example of this process is the many empirical studies that have been completed based on the Tinto model for retention. Over a 30-year period, Tinto has revised his model based on the results of the empirical studies.

2.2 Models of Engineering Student Success

In the development of a model that suggests that engineering success is different from (general) college success, I found three models of engineering retention or success. They are discussed in this section.

The Pipeline Theory

The pipeline model envisions a leaky pipeline with the leaks representing attrition from middle school to graduation from an engineering college. (See Figure 2-2)

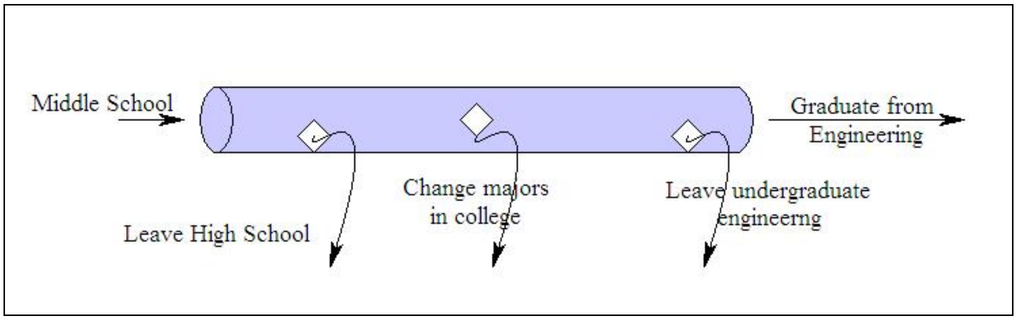

Figure 2-2: Pipeline Theory

Johnson and Sheppard (2002) discussed an example of the application of this model. In their paper, the authors looked at the pipeline structure of the high school senior class of 1990 (nationally) as they made decisions to go to college, enroll in an engineering college and graduate including an analysis by gender and ethnicity. Of the 1990 high school senior class, 87% graduated from high school; 28% enrolled in 4-year colleges; only 2.3% enrolled in engineering programs; and only 1.6% graduating with an engineering degree. Their review of studies led them to state, "HS [High School] preparation and lack of finances are two key factors that cause the differences in the enrollment rates between underrepresented minority students and other populations." The pipeline theory was useful for conceptualizing the loss of students from high school through engineering graduate school, but a more theoretical basis is needed for understanding why students decide to stay or leave the engineering field.

The Path Model

Adelman proposed that the correct model was not a pipeline but a path model. (Adelman, 1998) The courses taken in high school in math and science are similar for both engineer and science/math majors. Since the freshman courses in engineering include chemistry, physics and math, students may switch to a science major with little loss of time in major. This model supported the competitiveness of the STEM programs in attracting students. Adelman viewed the decision as a competitive one among several choices. The path model gave a better understanding, but still is weak in understanding why students decide to stay or leave engineering.

The Transmission Line Model

The most recent development of an engineering student success model has been proposed by Watson and Froyd and is focused on a model to increase diversity in engineering colleges (Watson and Froyd, 2007). They discussed that the pipeline theory may be used to conceptualize why there is not more diversity in the engineering student body. Instead of viewing the pipeline as longitudinally in time as in Figure 2-2, the "leaks" from the pipeline can be viewed as reasons for leaving. For example, the 'leaks" can be "not cognitively prepared" or "a sense of isolation." They discussed the number of intervention programs for underrepresented minorities, and indicate that they fall into three areas to address the pipeline leaks:

- *Stop Leaks*: (Community Building) Build Community through organizations or networks for the underrepresented participants so that they can help each other.
- *Stop Leaks*: (Cognitive Ability Development) Understand the 'weaknesses" in the cognitive abilities of underrepresented groups as a whole and intervene to strengthen these weaknesses.
- *Increase Intake*: (Occupational Choice Development) Increase exposure of underrepresented groups to engineering practice and careers."

The community building interventions develop an individual's sense of self-identity; cognitive ability interventions develop an individual's cognitive ability especially for under-prepared students in engineering, and occupational choice interventions such as a course on engineering courses develop self-identity as an engineer. Watson and Froyd proposed that the pipeline theory was too simple; that there are significant interactions between self-identity, career identity and cognitive ability. Interventions are often added onto a system that already exists. Rather than use a pipeline, Watson and Froyd use a transmission line because it represents the transfer of energy among the three main components of the transmission line: cognitive ability development, occupational choice development and self-identity development. (See Figure 2-3) Here the curriculum is most closely tied to the cognitive ability development.

The distribution of personal energy was important in this model. They stated: "Energy that might have been channeled into academics is siphoned into energy for identity development. Students who can delay these developments to focus on academics may be advantaged in academic reward systems, but not necessarily in their maturity and preparedness to work in a diverse world." They argued that in order to minimize loss of energy, balance between these three strands of the transmission line must exist. All three developments (cognitive, self-identity and career development) must develop together. The model supported a smoother integration of the current intervention programs into the curriculum. For example, career development as an engineer is continuous throughout the student's engineering undergraduate program, not just in the freshman year prior to making a decision about an engineering major.

Figure 2-3: Transmission Line Model (Adapted from Watson and Froyd, 2007)

As a new theory, the transmission line theory has merit. I especially liked the idea of strong interactions between cognitive development, self-identity, and identity as an engineer (career identity) and this theory influenced some of my empirical hypotheses.

2.3 Education Theories and a Review of Tinto's Model

In the development of a model for freshman engineering retention, two approaches may be taken:

1. Develop a new model based on learning theory
2. Revise an existing model

The engineering education models, discussed in Section 2.2, did not provide the detail related to the academic and social backgrounds of engineering students that I wished to study. I found there were other models in the education research literature. My interest in this research was primarily to develop systemic recommendations that would help students succeed; the development of a model was secondary. If a model already existed that included the effect of pre-college characteristics, my research would benefit from any empirical studies related to that model. With the number of models that have already been developed by education researchers, I decided to pursue revising an existing model. Models of particular interest will be discussed next.

General College Success Theories

Education researchers for (general) college student retention and success have developed the most comprehensive theories on general college student success. A summary of these theories are presented in Table 2-1 and all are oriented towards general college attrition. These theories of why students leave college without a degree were based on theories in four disciplines: economics, psychology, sociology and organizational theories (Braxton and Hirschy, 2005).

Table 2-1: Summary of Education Theories on Student Success

Researcher	Name of Theory	Main Points
Alexander Astin	Theory of Involvement	• Empirically based on HERI longitudinal study • Persistence related to student involvement • Behavioral model
John Bean	Theory of Student Attrition	• Importance of interaction with faculty • Working off-campus leads to attrition
Vincent Tinto	Interactionalist Theory of Student Departure	• Separation from home environment and integration into college environment • Importance of integration into environment both academically and socially • Persistence related to student involvement, including interaction with faculty and other students • Based on experiences, student changes goals

Source: Berger and Milem (1999)

The most accepted theory is that of Vincent Tinto (Braxton, 2000). Braxton noted, "Tinto's Interactionalist theory, nevertheless, enjoys near paradigmatic stature in the study of college student departure." Based on a review of the theories presented in Table 2-1 and the reputation of the Tinto model, substantial effort was taken to review Tinto's model and revise it to a working model for freshman engineering success.

Tinto's Model

In his theory that was developed in the 1970's and then revised to take into account the results of empirical studies, Tinto presented a process of adjustment of a new student to college (Tinto, 1993; Tinto, 2006). First, a student needed to separate from his family environment and then adjust to the college culture. In this adjustment, a student came to college with a set of pre-college characteristics and career and college goals. As he/she adjusted to college, a process of both academic and social integration was needed for the successful integration of the student. Academic integration was defined broadly as doing well in courses and social integration included both social relationships with other students and discussions with faculty. As academic and social integration occurred, a student reaches a new level of learning. This level of learning translated into value-added education, student success and potential persistence. In this adjustment, a student came to college with a set of career and college goals. As integration occurred, a student may change his/her goals for college with respect to a major or career.

Tinto's model was based on a four-year college experience. Compared to a model on freshman student success, in Tinto's model, academic and social integration was a larger part of the theory and pre-college characteristics were minimized. This emphasis on academic and social integration has led to discussions among educators of whether academic or social integration is more important. Braxton, in his review of Tinto's model using current empirical studies, found little support for academic integration but much support for social integration (Braxton, 2000). This is consistent with Astin's model on the importance of the involvement of the student in college activities (Astin, 1984). However, other empirical studies have found support for academic integration (Scalise, et al., 2000; Allen, 1999; Munro, 1981; Getzlaf et al, 1984).

In his original model, Tinto conceptualized that a good institutional fit (the fit between the student and college/university) was the responsibility of the student. If either the student did not have strong academic or social integration into the institutional culture, he/she was at risk of dropping out. Over time, the theory changed to recognize that the educational institution has the responsibility to make the culture welcoming to all students who have been admitted to the institution (Tinto, 2007).

The difficulty with the concept of academic and social integration was that the concept does not naturally lead to an effective institutional action. Tinto indicated: "What is needed and not yet available is a model of institutional action that provides guidelines for the development of policies and programs that institutions can reasonably employ to enhance the persistence of all their students" (Tinto, 2006). He has argued that a high level of institutional commitment leads to high expectations, which leads to a high level of support. This together with feedback and involvement leads to more effort by the student in learning; this ultimately leads to student success (Tinto, 2005, p. 326). Although Tinto did not define quality, his writings support Fiegenbaum's definition of value-added quality from the quality field (Kubiak, 2005).

Particularly relevant to a model on freshman student success, Tinto's model stressed the importance of engagement of students in the classroom by professors of freshman courses (Tinto, 1993; Tinto, 2006). This is the main contact of engagement between faculty and students for academic integration and integration into the institution's culture.

2.4 New Model and Explanation

Using Tinto' model as a basis, a new model of freshman engineering success was developed. This includes a model for both academic success and retention and is displayed in Figure 2-4.

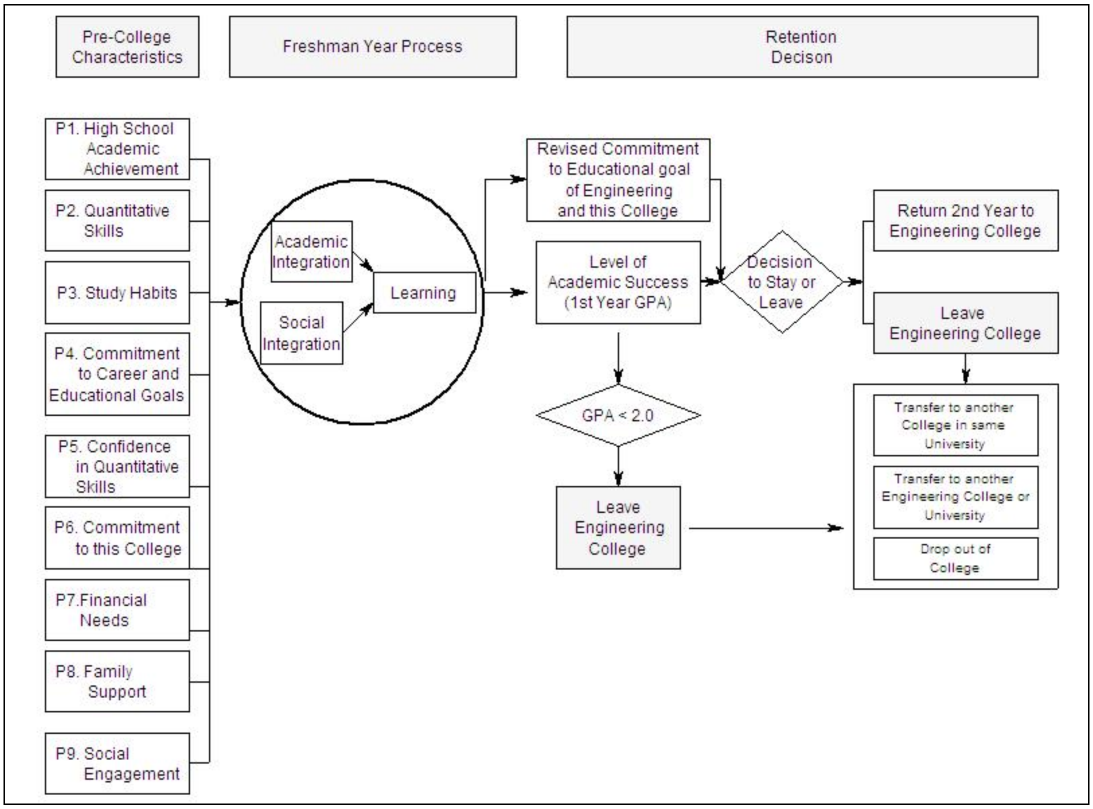

Figure 2-4: Block Diagram of Model of Freshman Engineering Student Success

The block diagram was divided into three stages for student success and will be discussed in the following sections:

2.4.1 Pre-College Characteristics

2.4.2 The Freshman Year Process, leading to successful learning as a student

2.4.3 The Retention Decision by the student at the end of the freshman year: to either stay or leave engineering

2.4.1 Pre-College Characteristics

This section discusses the pre-college characteristics that informed the engineering student success model. The process for the development of the model's pre-college characteristics was based on :

- a literature review of both engineering education literature and education literature (Sections 2.4.1.1, 2.4.1.2, and 2.4.1.3)

- the development of a list of hypothesized differences between engineering and other disciplines with respect to student success (Section 2.4.1.4)

With respect to the literature review of the pre-college characteristics, Section 2.4.1.1 describes the literature review process and sources for the literature review; Section 2.4.1.2 compares the findings of the literature review to Tinto's model; and Section 2.4.1.3 then discusses the findings of the literature review.

2.4.1.1 Literature Review Process

Figure 2-5 illustrates the process of conducting the literature review. To develop a model, I first reviewed Tinto's model, which was based on the entire college experience (four years) and considered revisions for a model for freshman success and retention. Note that the pre-college characteristics were considered more important in the proposed freshman success model than in Tinto's four-year model. Next, I reviewed Tinto's model with respect to a model for engineering retention.

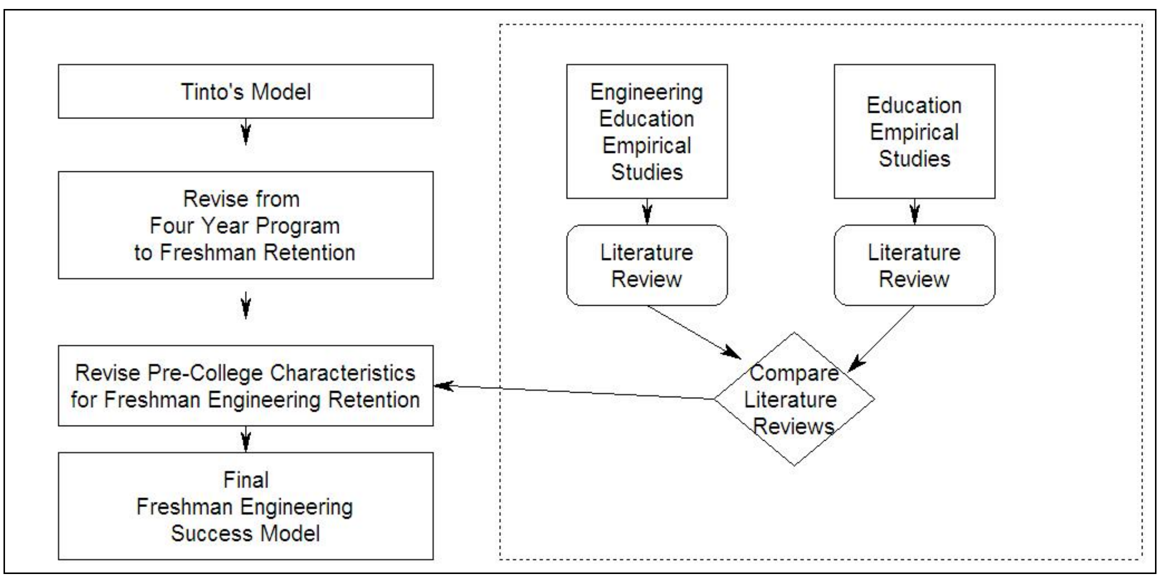

Figure 2-5: Development of Freshman Engineering Success Model

With model-building, it is typical to start with a wide net of possible variables that could be predictors for the model. Because of the few freshman engineering student success papers that were available in the literature, I expanded my literature review to include the education research literature and four to six-year retention studies. From the literature review, a list of significant pre-college characteristics was developed. These significant predictors were then summarized into nine major categories and are referred to as the pillars of student success[2]. Pre-college characteristics from Tinto's model were used as a guide (see Section 2.4.1.2). The literatures sources for the literature review are given next.

Literature Sources

In selecting research literature to review, the following research strategy was used.
Both multi-institutional and single-institutional research was used. Empirical studies that included an analysis of the relationship of pre-college characteristics to the following retention subjects were reviewed:

1. 1st year student success (college GPA)
2. first year through 2nd year retention
3. student success for 3rd year through graduation (cumulative college GPA)
4. 3rd year retention through graduation (retention or graduation rate)

Specific to Engineering Education retention research, the following sources were reviewed:

1. For the past ten years (1997 to present), papers in the ASEE Journal of Engineering Education (JEE) and the ASEE conference Proceedings; and for the past three years, the Conference Proceedings of the Frontiers in Education Conference.
2. "Undergraduate Science Education: The Impact of Different College Environments on the Educational Pipeline in the Sciences", which describes the UCLA/ Higher Education Research Institute (HERI) longitudinal study conducted under the direction of Alexander and Helen Astin (Astin and Astin, 1992). Also relevant papers on engineering student retention published by HERI researchers.

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[2] The idea of using the term "pillars" was adopted from "pillars of total quality education" in Cokeley et al. (2006).

3 *Talking about Leaving* by Seymour and Hewitt (1997).

In the engineering education literature, the articles on empirical studies of freshman engineering student retention generally fall into two areas: the relationship of pre-college characteristics to freshman retention and the effect of a change in teaching strategy, course development (such as an Engineering 100 course) or student support service such as mentoring on freshman retention. Only literature with a research focus on the effect of pre-college characteristics were considered.

Specific to Education retention research, the following sources were reviewed:

1. Four-year college studies included in Braxton's study of Tinto's model (Braxton,(2000), Tables 7 and 8, pp. 20-22)
2. Tinto (1993, 2005, 2006)
3. A summary of a meta-analysis study of 109 studies (Lotkowski et al., 2004). The details of the meta-analysis are in Robbins, et al. (2004)
4. Selected UCLA/HERI studies related to college student retention
5. Selected articles from *Journal of College Student Retention*

Because of the volume of education literature studies, this selection was considered as a representative sample in the education field, and in particular, representative of the study of Tinto's model.. It should be noted that the papers referenced in the Braxton study were mostly studies of four-year retention focused on the issues of social and academic integration during the college experience. For four year studies, it is logical that social and academic integration becomes more important compared to the pre-college experience. The meta-analysis of 109 retention studies by Lotkowski et al. (2004) was of particular significance in my research for the general education retention studies. Empirical studies specific to one gender or ethnicity were not included. In addition, empirical studies specific to one college course were not included.

Differences were observed between the predictors of student success for engineering education studies compared to education studies. Only the engineering education studies included predictors for academic success or retention that were related to quantitative skills or confidence in quantitative skills. On the other hand, mostly the education studies showed predictors related to commitment to this college or family support.

2.4.1.2. Pre-College Characteristics in Tinto's Model

Tinto's definitions of pre-college characteristics were used as a guideline to define a set of categories for pre-college characteristics. In *Leaving College,* he wrote about the importance of pre-college characteristics and goals and commitments:

> "Individuals enter institutions of higher education with a range of differing family and community backgrounds (e.g., as measured by social status, parental education, and size of community), a variety of personal attributes (e.g., sex, race, and physical handicaps), skills (e.g., intellectual and social), financial resources, dispositions (e.g., motivations; intellectual, social, and political preferences), and varying types of pre-college educational experiences and achievements (e.g., high school grade-point average)…Intentions or goals specify both the level and type of education and occupation desired by the individual. Commitments indicate the degree to which individuals are committed both to the attainment of those goals (goal commitment) and to the institution into which they gain entry (institutional commitment). " (Tinto, 1993, p. 115).

In Tinto's model, goals and commitments were considered as a separate category from "pre-entry attributes." In my revised model for freshman engineering success, goals and commitments were included as pre-college characteristics with the rationale that a student comes to college with an initial set of educational and career goals and therefore were considered as a pillar of pre-college characteristics. Since I was interested in proposing a model that would work for both genders and all races, gender and race were not included in my model.

Table 2-2 presents a comparison of Tinto's pre-college characteristics to my findings from the literature review.

Table 2-2: Pre-College Characteristics Important for Engineering Student Success

Pillar	Pre-College Characteristic Pillar	Tinto's Suggestion (1993)	Predictors of Student Success In Empirical Studies
1	High School Academic Achievement	Intellectual Skills Pre-college Educational experiences Pre-college educational experiences and achievements including the high school GPA	H.S. GPA or H.S. Rank ACT Composite or SAT Total Academic self-confidence Communication Skills
2	Quantitative and Analytical Knowledge	Not defined	ACT Math or SAT Math Math or Science preparation (instrument other than ACT or SAT);High School years of math
3	Study Habits	Study Skills	Study habits Hrs/week studied in high school Time management skills Came Late to Class Overwhelmed
4	Education and Career Goals	Motivation and goal attainment Level and type of education and Occupation desired; Intellectual, social and political preferences	Education and Career Goals Drive to Achieve/Motivation Engineering specific: Like Engineering Started as freshman in engineering Family member is an engineer Financial benefits/ influence of engineering Good impression of engineering Strong scientific orientation
5	Confidence in Quantitative Skills	Not defined	Self-rating or confidence in math, science or computers Confidence in engineering skills Enjoy math or science Orientation towards science
6	Commitment to this (Enrolled) College	Institutional Commitment	Choice of College Reason for choosing this college Satisfaction with choosing this college
7	Financial Needs	Financial resources	Amount of loans Scholarship indicator Working in high school indicator
8	Family Support	Social Status Parental education Size of Community	Education level of parents Income level of parents Social Status
9	Social Engagement	Social Skills	Social involvement; connectedness with teachers and other students Participate in community/clubs

The third column of Table 2-2 displays the pre-college characteristics as described by Tinto (above) and the fourth column provides a comparison to the literature review based on the nine pillars of student success.

The predictors of student success for the second pillar, Quantitative Skills, and the fifth pillar, Confidence in Quantitative Skills, were found only in the engineering education literature. The literature review provided more definition to Tinto's initial list of pre-college characteristics and goals.

Next, the discussion of the literature for each student success pillar of pre-college characteristics follows. For each pillar, the more relevant articles that influenced my thinking on the pre-college characteristics pillar are discussed.

2.4.1.3 Literature Review Shows Support for Pre-College Characteristics

P1. High School Academic Achievement

For this pillar, both academic performance and non-academic variables (e.g. self-confidence) were considered from the literature.

Strong Support for Academic Variables as Predictors

There was consistently strong support for the academic variables high school GPA and high rank. High school GPA was a significant predictor for freshman engineering academic success or retention studies (Levin and Wyckoff, 1988; Lackey et al., 2003) and for freshman education academic success or retention studies (Glynn et al., 2005; Williamson and Creamer, 1988) Burtner (2004) found a significant difference in the average high school GPA between students who returned and students who left after one year of engineering college. High school GPA was also a significant predictor for upper-class engineering academic success or retention studies (Astin and Astin, 1992; Zhang et al., 2004) and upper-class education academic success or retention studies (Monroe, 1981; Getzlaf et al., 1984; Stoecker et. al., 1988; Astin and Oseguera, 2005). High school rank was a significant predictor for freshman engineering academic success or retention studies (Besterfield-Sacre, et al., 1997; Scalise et al., 2000) and for freshman education academic success or retention studies (Terenzini et al., 1985; Allen, 1999). High school rank was also a significant predictor for upper-class engineering academic success or retention studies (Moller-Wong and Eide, 1997; Besterfield-Sacre, 2002; French et al., 2005,). Only the Scalise et al. (2000) showed support for the SAT Total as a predictor of freshman engineering retention; more support for either the SAT Total or ACT Composite as a significant predictor was evident in the freshman education (non-engineering) academic success or retention studies (Tinto, 1993; Terenzini et al., 1985; Pike et. al., 1997) For the upper-class academic success and retention studies, the engineering education studies (Padilla et al., 2005; French et al., 2005; Moller-Wong and Eide, 1997) and the education studies (Tinto, 1993; Astin and Oseguera, 2005) showed support for the SAT Total or ACT Composite scores as significant predictors. In addition, in their meta-analysis of 109 studies on postsecondary retention, Robbins, et al., identified the High School GPA, and ACT scores as strong predictors of college GPA. (Lotkowski, et al., 2004; Robbins, et al., 2004). Of the academic variables, Robbins, et al. concluded that the high school GPA and ACT scores have the strongest relationship to college GPA. They also concluded that the strongest variable for college retention was the high school GPA. A recent multi-institutional study by Astin and Oseguera (chapter 9 in Seidman, 2005) gave independent evidence of the strength of the high school GPA; they wrote, "Clearly, the pre-college characteristic that carries the most weight in estimating the student's chances of completing college is the high school GPA."

Moderate Support for Non-Academic Variables as Predictors

Most of the support for non-academic factors was found in the education retention studies. Robbins identified academic self-confidence as a strong predictor of both college GPA and college retention (Lotkowski, et al., 2004; Robbins, et al., 2004). Some support was found in the engineering education literature. In the Besterfield-Sacre et al. (1997) study, support was found for a survey question on self-assessed confidence in writing and speaking skills as a significant variable for attrition of engineering students in good academic standing. In this study, students who left engineering college had high average scores on communication skills compared to students who stayed in engineering and students who left engineering due to a poor academic standing.

P2. Quantitative Skills

Strong Support in the Engineering Education Research for the SAT Math or ACT Math Scores as Predictors of Student Success

Support for the ACT Math or SAT Math as significant predictors of academic success or retention was found, almost entirely, in the engineering education research literature. This is a major difference between the engineering education and education research on academic success and retention. From the freshman engineering education empirical studies, there was strong support for the ACT Math or SAT Math as a predictor of freshman engineering academic success or retention (Besterfield-Sacre et al., 1997; Levin and Wyckoff, 1988; Lackey et al., 2003; Leuwerke et al., 2004). For the upper-class engineering education empirical studies, there was strong support the ACT Math or SAT Math as a predictor of academic success or retention (Astin and Astin, 1992; Moller-Wong and Eide, 1997; Besterfield-Sacre, et al., 2002; Zhang et al., 2004; French et al., 2005). There was also support for placement test scores (Levin and Wyckoff, 1988; Budny et al., 1998; Besterfield-Sacre et al., 2002) in the engineering education literature. For all majors in his multi-institutional study, Adelman found that "the highest level of mathematics one studies in secondary school has the strongest continuing influence on bachelor's degree completion" (Adelman, 1992). Supporting this, a recent study by Astin and Oseguera (2005) showed that the number of years of high school math was a significant predictor of graduation rate (using a CIRP database at HERI/UCLA).

P3. Study Habits

Strong Support in Literature

The literature review of the freshman engineering education research showed that study habits and the number of hours/week a student studied in high school were important pre-college characteristics of academic success or retention (Levin and Wyckoff, 1988; Besterfield-Sacre, et al., 1997; Scalise et al., 2000; Burtner, 2004). In addition, for the general college freshman student studies, support was also found for study habits (Donovan, 1984, Glynn et al., 2005 Tinto, 1993). Support was also found for good study habits from high school as a predictor of student retention. Astin and Oseguera (2005) found hours spent in high school studying as a significant predictor of six-year graduation. In their meta-analysis, Robbins, et al. (2004) found "time management skills, study skills, and study habits" as a strong predictor of college retention and a moderate predictor of college GPA (academic success).

In a structural model, French et al. (2003) found that 3- to 4-year retention in engineering was negatively affected by integration with faculty (talking with faculty), and positively affected by integration with students (talking with students). This suggested the importance of learning teacher and student engagement in high school. Astin and Oseguera (2005) found that the frequency of talking with a teacher outside of class (positive effect) was a significant predictor of retention. Glynn (2005-2006) found his factor Good Habits, that was highly loaded with "Saw teacher for help," "Studied with friends," and "extra credit" in high school was significant for four cohorts on student retention.

Daempfle discussed the importance of being an independent learner in college, compared to high school. In consideration of the intensity of freshman engineering courses, students who are already independent learners with good study habits will earn better grades compared to students who are not independent learners. For an engineering education, Tribus indicated that being an independent learner was especially important. With increased autonomy, the student develops an attitude of "joy in learning" and intrinsic motivation (Tribus, n.d.). Support for the importance of independent learning also came from the Astins: "When students see themselves, or are viewed by others, as both learners and teachers, they take more responsibility for their own learning and help create more favorable learning environment for each other." (Astin and Astin, 2000)

Frequency of coming late to class in high school (a CIRP variable) was considered as a negative contribution to learning in the high school or college classroom and was included in this pillar. Shumann, et al. found a significant difference ($p<.010$) in the percent of students placed on probation for the first term of engineering college between students who had a high frequency of coming to class late in high school and students who had a low frequency (Shumann, et al., 2003). In a 303-college HERI study for entering freshmen in 1994, Oseguera (2005-2006) also found support for the significant of this variable for college four- and six-year retention.

One of the CIRP variables included in this pillar was related to "feeling overwhelmed" in high school. Shumann et al.(2003) found support for the being overwhelmed as a possible contribution to freshman engineering attrition. In a survey conducted with students who transferred out of engineering, the question was asked: "were you emotionally prepared for the stress of the curriculum?" Thirty-seven percent of the freshmen leaving engineering responded "no" to this question.

P4. Commitment to Career and Educational Goals

Strong Support in Literature

Sources from both engineering education and education research supported the importance of a commitment to career and educational goals. Engineering education researchers. found that students who had a high impression of engineering and liked engineering as a career had a higher freshman retention rate (Besterfield-Sacre et al., 1997; Burtner, 2004, Hartman and Hartman, 2006). In addition, Levin and Wyckoff (1988) found that a positive attitude towards engineering significantly affected the college GPA; Students with an "intrinsic" interest in engineering tended to have a higher GPA (.14 difference) than students who choose engineering for high pay and status. Astin and Astin (1992) found that students who are oriented towards a scientific career (i.e. important to make a theoretical contribution to science), and who indicated their most probable career was to be an engineer (as freshmen), tended to persist to graduation in engineering. This was supported by the Moller-Wong and Eide (1997) study. A significant predictor of graduation in engineering is starting in engineering as a freshman (Astin and Astin, 1992; Johnson and Sheppard, 2002). In addition, it was found that there was a higher probability of a student graduating in engineering if his/her peers are in engineering. Support was found for having a father who was an engineer (Astin and Astin, 1992; Seymour and Hewitt, 1997). Some engineering students who primarily entered engineering college because of the financial influence of good pay tended to switch to another major, especially if they did poorly academically (Seymour and Hewitt, 1997; Besterfield-Sacre, et al., 1997).

For freshman non-engineering retention studies, it was found that academic goals are highly significant for college retention. (Robbins, et al., 2004) Using the CIRP survey, Astin and Oseguera (2005) found the self-rating on drive to achieve and going to college to prepare for graduate school were a significant predictors of upper-class college retention. French et al. (2005) also found that motivation was a significant predictor of upper-class retention of engineers.

With respect to freshman retention in engineering, Leuwerke et al. (2004) explored the relationship between math knowledge as measured by the ACT Math and the Hexagon Congruence Index (HCI). In this study, the HCI measures the congruence between individual interests and an engineering career. 844 students from one university were involved with this study. They found:

- It is not sufficient to have a strong congruence (interest) in engineering for retention in engineering; instead, retention in engineering is "within the context of mathematics achievement." Students with higher ACT Math scores tend to stay in engineering regardless of the congruence to engineering. An ACT Math score of 26 is indicated as a threshold for a high probability of retention.
- For students with strong math scores, efforts to "increase these student' interests in the field could improve retention rates." The authors indicated that this is supported by social cognitive career theory.
- Students who left engineering had lower ACT Math scores, lower college GPAs and lower congruence with engineering.
- Based on their analysis, there were no differential attrition rates in engineering attrition rates for female and minority students. They hypothesized that "it s not gender or ethnicity but interests that affect motivation to pursue an engineering degree".

P5. Confidence in Quantitative Skills

Strong Support in Engineering Education Literature

Questions on confidence in quantitative skills, such as self-rating of math ability usually were significant for only the engineering education studies. In the multi-institutional education studies that used the CIRP survey, the self-rating of math ability was not usually significant. Using the CIRP survey, the Astin and Astin study showed that a high self-rating in mathematical skills was related to retention in engineering. (Astin and Astin, 1992)

Using the PFEAS © survey, Besterfield-Sacre et al. studied freshman engineering retention at the University of Pittsburgh and showed that confidence in basic engineering skills increased freshman retention. Besterfield-Sacre et al. and Burtner also showed that the pre-college characteristic of enjoying math and science was important for freshman engineering retention. (Besterfield-Sacre et al., 1997; Burtner, 2004)

P6. Commitment to This College

Strong Support in Education Literature

Commitment to the enrolled college includes the college choice by the student. Although there was very strong evidence of commitment to the enrolled college as a predictor of retention in the education retention studies, there was minimal evidence of its importance in the empirical engineering studies. In the Astin and Astin multi-institutional study (1992), choice of college was not significant for persisting in an engineering career.

The education research first year retention studies showed "commitment to the university" as having a strong relationship to first year retention or college retention (Pascarella and Chapman, 1983; Glynn et al., 2005; Lotkowski, et al., 2004; Robbins, et al. 2004).

P7. Financial Needs

Financial Needs Influence Retention

Retention studies, both engineering education and education, showed support for financial needs as a predictor of academic success and student retention (Astin and Astin (1992);Brainard and Carlin (1998); Johnson and Sheppard, 2002) In a freshman retention study, having a scholarship was a significant variable for first term GPA (Besterfield-Sacre, 1997)

Using a causal model, Allen (1999) found that financial aid had a direct effect on freshman GPA, but not on retention. A recent HERI study showed that "concern about being able to finance college had a negative effect" on college retention. (Astin, 2005-2006).

P8. Family Support

Support by Family Important for Student Success

Seymour and Hewitt (1997) discussed the importance of family members in persuading students to enroll in science or engineering majors. Examples were cited of a student's father being a family member, of concerns expressed by parents of low paying jobs in other fields and students feeling obligated to their parents who were paying for college. Several education studies have shown the importance of family support of students (Elmers and Pike, 1997; Pike, Schroeder and Berry, 1997; Tinto, 2006). Some studies have found that the educational level of the parents, contribute significantly to retention in four- to six- year studies (Oseguera, 2005-2006; Glynn, 2005-2006). Astin and Oseguera (2005) found support for both the parent's educational level and parental or family aid for six-year college retention (formula 5).

Support was found for encouragement from friends and family being significant for retention (Cabrera, Nora and Castaneda, 1993). In support of these findings, Elkins, Braxton, and James (2000), in another education study, concluded: "Especially before and during the critical first semester, higher education practitioners should seek to involve parents, other family members, and friends in a variety of ways to provide assistance to students negotiating the separation process."

P9. Social Engagement

Strong Support in Astin's Theory of Involvement

Astin's Theory of Involvement stressed the importance of students becoming involved with activities within the university, including clubs and volunteer activities (Astin, 1984). The more involvement in activities, the more integrated the student becomes into the values of the institution. In a recent HERI 6-year study, "participate in volunteer/community service work" was significant for college retention. (Astin and Oseguera, 2005) In their meta-analysis, Lotkowski, et al. (2004) found a moderate relationship between social involvement (defined as "extent to which a student feels connected to the college environment, peers, faculty, and others in college, and is involved in campus activities) and college GPA and retention.

2.4.1.4 Hypothesized Differences Between the Freshman Engineering Curriculum and Other Freshman Programs that Influence the Development of a Model of How Freshman Engineering Student Success is Different

In addition, to the literature review, hypothesized differences between engineering and other disciplines were considered and their influence on the development of the pillars of student success. This section discusses the development of a theory of how engineering student retention is different in preparation for development of a model on freshman engineering success. The discussion follows below.

Role of the Engineering Professional Program

The role of an undergraduate bachelor program is to prepare an engineering student for an engineering career. Engineering is one of several pre-professional and professional programs at the undergraduate level to prepare a student for a specific career. Besides engineering, education (teacher), business, pre-medicine, and pre-law are considered as pre-professional or professional programs in the university environment. This leads to a need to have a "commitment to career goals" in a student success model. Some of these pre-professional and professional programs have a closer freshman curriculum to engineering than others. For example, both engineering and pre-medicine require enrollment in science courses and math courses (either calculus or statistics) in the freshman year. In contrast, pre-law and business would have more focus in the social sciences in the freshman year. Majors in the liberal arts or sciences focus less on a career, especially in the freshman year.

Role of Engineers in Society is That of a Designer or a Technology Problem-Solver

To understand the engineering curriculum, it is important to understand the role of engineers in society. In becoming a competent engineer, the function of an engineer in society is that of a designer of a new product or system or problem-solver. Typically, engineers are involved with defining or using the latest technology. Engineering is also seen as the profession that will create the latest innovation in technology or the innovation-makers. In manufacturing, this includes designing the manufacturing processes for the component or assembly. In quality engineering, this includes designing the processes (both technical and human interfaces) that assure that the manufactured product meets the design's intent. In summary, an engineering student is preparing for a career as an analytical thinker who can lead people in innovation, design and systems thinking.

Engineering Curriculum Stresses Mathematics and Science

The courses most strongly related to analytical thinking n technology are mathematics and science courses. The engineering freshman curriculum is weighted with mathematics and science courses and of all disciplines, the engineering students take the most mathematics and science courses in their freshman year. Expectations for admissions to an engineering program will include a wide range of college-prep courses with a large number of math and science courses (due to the need to develop analytical skills). The science and math majors take the same freshman level science and math courses as engineering students. Therefore, it is expected that their success and retention rates will be the most similar to engineering students. The difference between these two student groups is that engineering students also enroll in freshman engineering classes, which also have a high math and science content. The largest difference would be seen between engineering students and liberal arts majors (almost no math and science courses). In summary, an engineering education is considered uniquely different from the other pre-professional or professional programs or the liberal arts, leading to different retention issues.

Competitive Grading in Freshman Engineering Classes

Seymour and Hewitt (1997) have discussed the weeding-out system that is common in engineering colleges, especially for the freshman engineering courses. In addition, the Astin and Astin study found that engineering students earned lower college GPAs than other students (Astin, 1993). Students with a stronger math and science background will have a competitive advantage, whereas students with a weak math and science background may have a competitive disadvantage. There is a stronger need for institutional support of students in achieving academic success in the first term.

Hypothesized Differences between Engineering Freshman Curriculum and other Freshman Programs

Based on these four concepts, four differences are hypothesized between the engineering freshman curriculum and other freshman programs that influence the development of a model of engineering student success:

1. A major in engineering prepares a student for a specific career, that of an engineer; the other pre-professional and professional programs also prepare a student for a specific career in their program. Majors in the liberal arts or sciences focus much less on a career.
2. The focus of the freshman-engineering curriculum is on developing strong analytical skills and problem-solving using technology; the engineering curriculum is the most intense with math and science courses in the freshman year.
3. Expectations for admissions to an engineering program include a wide range of college-prep courses with a large number of math and science courses (due to the need to develop analytical skills).
4. A competitive grading system is common in engineering colleges. As a result, the freshman-engineering curriculum tends to be very competitive. Those

students who have the stronger pre-college preparation in math and science will have an advantage. There is a stronger need for institutional support of students in achieving academic success in the first term.

These four differences were applied to support the model for freshman engineering success. The first one was that engineering students were more focused on a career than most other disciplines. This difference is supportive of the P4 pillar: Commitment to Career and Educational Goals. The second difference was a curriculum focused on developing strong analytical skills using technology. This difference is supportive of the P2 pillar: Quantitative Skills. The third difference was that admissions is based on a wide range of college-prep courses, including a large number of math and science courses. This difference is supportive of the P1 and P2 pillars: High School Academic Achievement and Quantitative Skills. The fourth difference was a competitive grading system. This difference is supportive of all the pillars. Support in all the pillars for student success will enable an engineering student to be more prepared for academic success and retention in a competitive grading environment. The pillars most directly related to grades are P1, High School Academic Achievement, P2, Quantitative Skills, and P3 Study Habits. The other pillars contribute indirectly to academic success in a competitive environment.

In summary, the literature review and the set of hypothesized differences inform the model into the development of the nine pillars for student success. These nine pillars can be thought of as a structure that is important for the support of all students.

2.4.2 The Freshman Year Process

In Figure 2-4, the Block Diagram includes a circle labeled as the Freshman Experience Community. Consistent with Tinto's model, it includes academic and social integration, which leads to a high level of learning and student success. Both "academic integration" and "social integration" are "abstract concepts that are basic to Tinto's model. (Tinto, 2006) Academic integration is defined broadly as doing well in courses and social integration includes both social relationships/leadership with other students and discussions with faculty. Both are needed for successful interaction between the student and the institution and the retention or persistence of the student. The student's experiences continually affect his/her commitment to his/her goals and the institution.

Unfortunately, in the reviewed empirical research papers, especially the papers used in the Braxton research project (Braxton, 2000); there was inconsistency in the definition of 'academic integration" and "social integration". In drawing any conclusions, a broad definition needs to be applied. However, in a very general sense, it may be strongly stated that there was a consistent validation of Tinto's model that integration and interaction between the student and, an institution's efforts at interaction or integration with a student leads to higher retention.

2.4.3 Retention Decision:

With the proposed model, the student is influenced by two elements of the model

- academic success, as defined by the first year GPA
- A revised commitment to an educational goal of an engineering degree and commitment to continuing at this college.

The Influence of Academic Success

This portion of the proposed model is a departure from Tinto's model. In the proposed model, there is a more specific emphasis on the first year GPA. Tinto's model is more general and does not appear to specifically identify the college GPA. Rather, his model recognized the importance of academic integration (doing well in courses) and this leads to learning, which leads to student success.

Empirical research strongly supported that the actual college GPA influences a student's decision whether to stay in engineering (Elkins and Luetkemeyer, 1974; Astin, 1993; Budny, 1998; French, et al., 2005; Burtner, 2004; Zhang, et al., 2006; Allen, 1999). In a study of 512 engineering freshmen at the University of Maryland, Elkins and Luetkemeyer found that the average first year GPA for students who returned to engineering was significantly higher than for students who left engineering. The Astin and Astin study (1992) found that engineering students earned a lower GPA than other college majors. Astin also found that "undergraduate GPA is the single most important determinant of students' aspirations for advanced degrees" and hypothesized that since engineering students earn a lower GPA than other majors that they are discouraged from applying to graduate programs (Astin, 1993). Budny, et al., (1998) reported a higher correlation between first year GPA and engineering retention than between high school rank or GPA and engineering retention. French et al. (2003) found that the college GPA was a significant predictor of engineering retention along with high school rank, the SAT Math score and a motivation score. In a logistic regression, the odds ratio for the college GPA was the largest with an odds ratio of 2.19. (95% confidence interval was 1.72 to 2.77.) Burtner (2004) found a significant average difference in the first year GPA of engineering students at Mercer University between those students who stayed and left engineering after one year. Zhang, et al. (2006) reviewed the relationship between the college GPA and retention at nine engineering colleges over fifteen years. They found that, within 3 semesters, most students with a low GPA had switched out of engineering. In this study, a very low percent of engineering graduates earned a first year GPA less than 2.0. As a result of their extensive research on the relationship between the college GPA and retention for engineering students, Zhang et al. stated, " We hypothesize the causal link that student self-efficacy improves with academic success and self-efficacy lead to improved retention. "

In a freshman non-engineering retention study conducted by Allen (1999), the first year GPA (i.e. student performance) had a direct effect on persistence for both minority and non-minorities. High school rank was a major predictor of the college GPA for all students.

Contrary to these studies, the Seymour and Hewitt study (1997) indicated no difference in academic performance between students who stayed, and students who left their STEM programs.

The Influence of a Revised Commitment to Educational and Career Goals

As the student takes courses in the first year, he/she re-evaluates his/her career and educational goals. This concept was initially adopted from Tinto's model, which recognizes that the student may change his/her college goals and commitment during his/her college experience (Tinto, 1993). In addition, Watson and Froyd's engineering education model reinforces its importance by describing this as "interference" or interaction between the cognitive performance, career goals and self-identity (Watson, 2007). Adelman's proposal of competing paths to a college major adds validity to this idea (Adelman, 1998). The model (see Figure 2-5) shows the student reaching a revised educational goal of either being interested in engineering as a major and career or in some other major, (usually in the science/math domain).

The student also re-evaluates whether he/she has commitment to the college in which he/she is enrolled. If the student is doing well and had integrated both academically and socially, the student will continue with high probability at this university, even if he/she changes major. If the student has not integrated well, he/she may switch universities or dropout without transferring to another college.

Engineering 110, a survey career on engineering careers at Michigan will be discussed in this research with respect to helping students decide on a career. Although there are papers in the literature on the effectiveness of an Introduction to Engineering course, I found no papers on the effectiveness of an engineering career survey course.

Four States of Retention (Decision to Stay or Leave)

This part of the model is more detailed than Tinto's model and specific to engineering. It is based only on retention at the end of the freshman year. We can summarize the decision made by the engineering student at the conclusion of his/her freshman year as one of four states. These are shown in Figure 2-4. The four states are:

A. The student decides to return to Engineering
B. The student leaves Engineering (due to academic probation or voluntarily leaves) and transfers to another college in the same university

C. The student is pushed out or voluntarily leaves Engineering and transfers to another engineering college or a non-engineering program at another university
D. The student decides he/she is not college material and drops out completely.

Student's Decision to Leave Due to Low Grades and Academic Probation

Leaving due to academic probation is more of a concern with engineering colleges. Astin (1993) found that the college GPA for engineering students was less than for other majors. Students who are marginally prepared in math or science are at risk of earning poor grades in a competitive grading system, Generally, students who earn less than a "C" average are placed on probation and within one or two terms, the student may decide to leave engineering or may involuntarily leave.

It should be noted that in comparing the proposed model to Tinto's model, Tinto's model is focused mostly on attrition due to voluntary leaving, not leaving due to academic probation. Tinto wrote, "the model pays special attention to the longitudinal process by which individuals come to *voluntarily* withdraw from institutions of higher education. Though the occurrence of academic dismissal will not be ignored, it will not be central to our discussions"(Tinto, 1993, p. 112) My general sense from the literature review was that leaving due to an academic probation status(i.e. the institution asking a student to leave) is much more prevalent in engineering studies than general college studies. (I reviewed some freshman retention studies that did not even address leaving due to a low GPA in the general college retention literature.)

Defining Loss to Society

From Industrial Engineering concepts, a loss can be conceptually described for each state of retention and is shown in Figure 2-6.

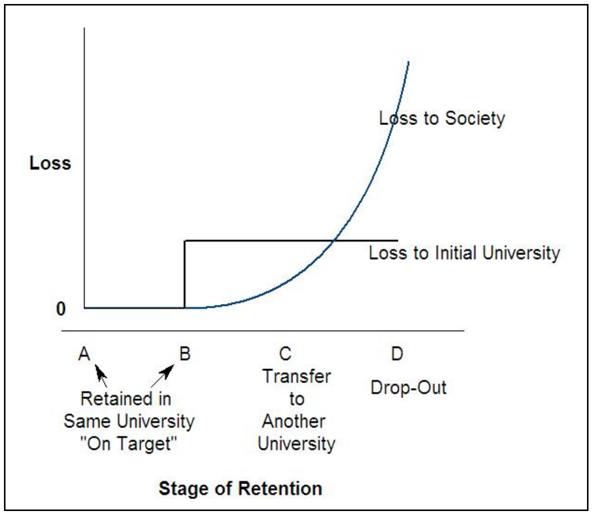

Figure 2-6: Loss Function Related to Retention/Attrition of Engineering Students

1. In States A and B, investment of the university in the first year is returned with the student returning to the same university and there is no loss; only gain in the potential of the student. The freshman year is a time of transition and if the student decides to switch to another college in the same university, this should be considered part of the retention process. Many students enter engineering college without a full understanding of an engineering career.

2. In State C, the student leaves the university and transfers to another engineering college or university. In Tinto's model of a good fit, the student has decided he/she is not a good fit for the initial university. The first university lost its investment in the student. On the positive side, the student is still pursuing a college degree and with the degree, he/she will add more value to society.

3. In State D, after one year of college, a student drops out. This is both a loss in the investment of the initial engineering college and university and to society. Instead of the student having an engineering career or other college-based career, he/she will potentially be limited to an entry-level position in the job market. The potential of the student will not be reached in either his/her education, earning power or value to society.

Using the ideas of institutional effectiveness, if a student leaves after one year, the educational institution loses three years of tuition. This tuition must be replaced by recruiting a transfer student. The loss of the student is also important to an institution.

Thus, both for the institution and the student, the initial loss of the student and loss of income by the institution can be traded off to the initial costs of significant retention intervention programs.

2.5 Summary

The thesis is that engineering retention is different from general college retention. Current engineering retention models were discussed and the development of a new model for freshman engineering retention was developed.

This model for freshman engineering student success was based on the concepts in Tinto's model. Tinto's model was used as the model's basis because it has a strong initial focus on pre-college characteristics. In addition, Tinto's model has been validated over the past 30 years and is well accepted by education researchers. The model of freshman engineering retention has three components that are shown in Figure 2-7:

1. Pillars of student success (Pre-College Characteristics)
2. The Freshman Year Process
3. The Retention Decision by the student

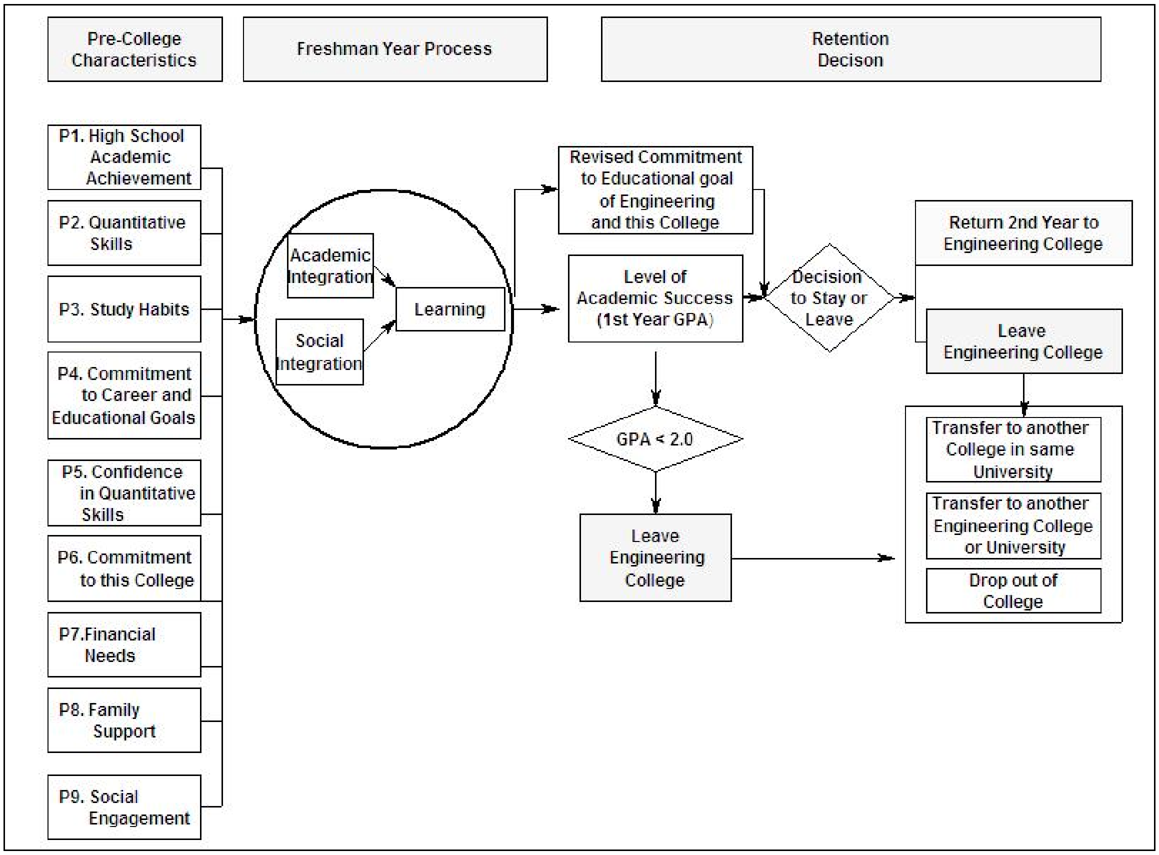

Figure 2-7: Model for Student Success

The literature review and the set of hypothesized differences informed the model into the development of the nine pillars for student success. These nine pillars can be thought of as a structure that is important for the support of all students.

Just as the Doric columns of the classic architecture of Angell Hall symbolize the strength of the University of Michigan campus and “give unity and form to the entire campus” [3], the pillars of student success define the structure needed for supporting engineering student success. (Figures 2-8 and 2- 9)

[3] Quote made by President Burton on the building of Angell Hall.
Source; University of Michigan, “A Historical Tour of the University of Michigan Library, http://bentley.umich.edu/exhibits/campus_tour/angell.php

Figure 2-8 : Angell Hall, University of Michigan

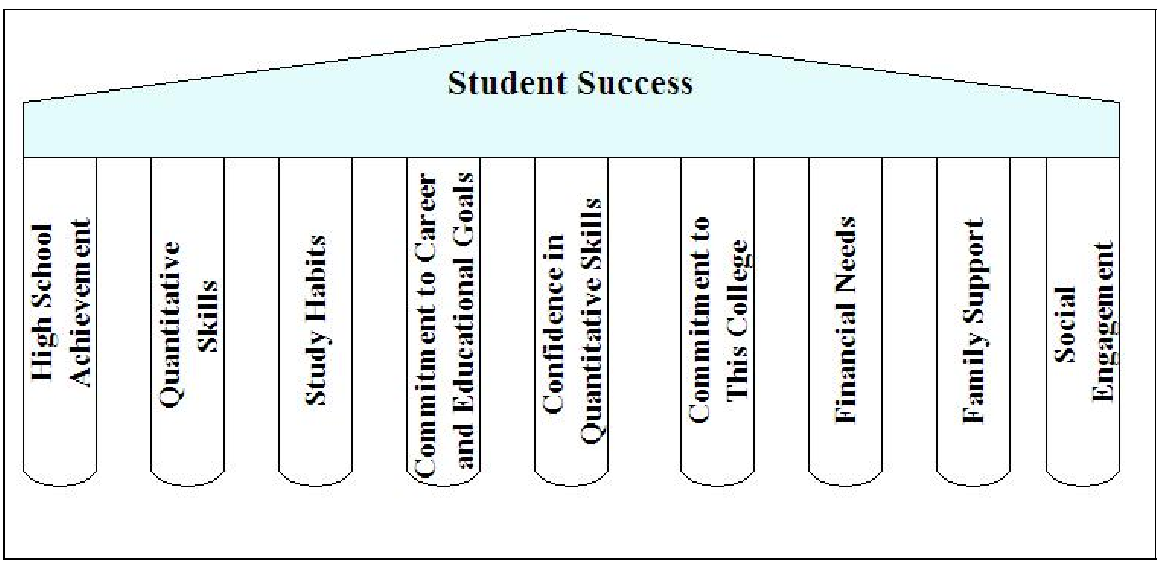

Figure 2-9 Nine Pillars for Student Success

Together with the pillars of student success, the freshman year of learning process and the retention decision, the model is defined for freshman engineering student success, both in terms of academic success and student retention. This model has the advantage over most models on engineering success in that it lends itself to empirical model building.

The concept of a loss function was discussed for student attrition. When students leave the university, a loss to the university and society may be defined. When a student drops-out, any institutional commitment to the student stops; leading to a high loss of human potential to society. This provided an argument for institutional responsibility for a high retention rate in order to minimize the loss of human potential to society.

CHAPTER III

VARIABLES AND DATA STRUCTURE

In Chapter II, a model for freshman engineering success was developed. This model includes nine pillars for student success. The variables selected for each pillar will be discussed in this chapter. In addition, this chapter summarizes the data management issues addressed in this research. The following data management elements significant to the empirical study will be discussed:

- Variables considered in the model's pillars (Sections 3.1 and 3.2)
- Calculation of the output variables from the model (Section 3.3)
- Definition of each student sector: Engineering, Pre-Med, STM and Non-STEM (Section 3.4)
- IRB Approval (Section 3.5)
- Response Rates from the CIRP survey (Section 3.6)
- List of Databases used for each analysis (Section 3.7)
- Definition of ACT and SAT Subsets (Section 3.7)

3.1 Overview of Selection of Variables

Chapter II defines the freshman engineering success model (see Figure 3-1) with the nine pillars of student success based on a literature review. This section defines that selection process.

The variables used in this study come from three sources:

- The UCLA/Higher Education Research Institute (HERI) Cooperative Institutional Research Program (CIRP) survey conducted during freshman orientation.

- The Michigan Administrative Information Services (MAIS) database which contains student performance data
- A research database for College of Engineering students; this database contained frequency of advising visits to the Engineering Advising Center.

These databases are discussed in more detail along with the IRB approval in Sections 3.5, 3.6 and 3.7.

For each pillar defined in the model, relevant variables from the CIRP data and MAIS data were selected. A complete list of variables is presented in Section 3.2.

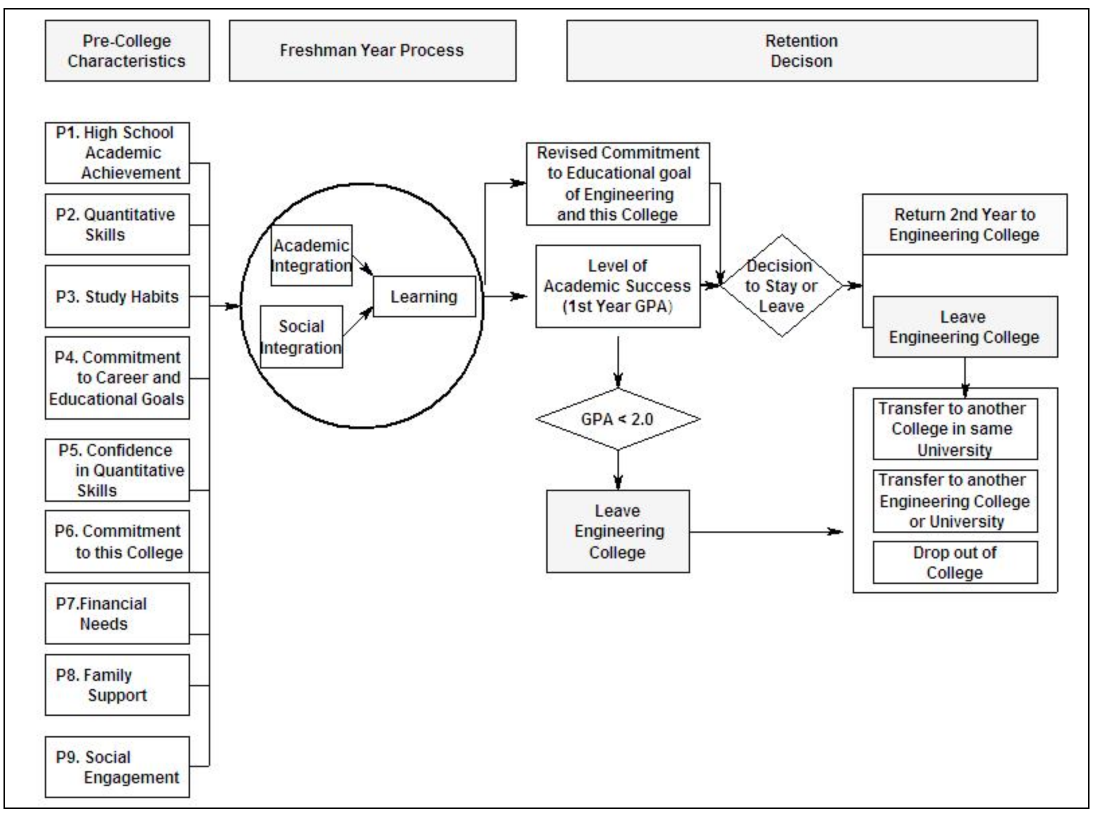

Figure 3-1: Model for Student Success

3.1.1 Selection of Variables

Most of the data management issues revolved around the selection of variables from the CIRP database. The CIRP database initially had about 300 variables. It asks incoming freshmen questions related to academic, religious and social background; parents' background; college and career plans; reasons for coming to college; abilities and traits measured by self-ratings; student attitudes on social issues; academic and social activities; aspirations; commitment to current major and career; and concern about financing a college education. Only CIRP variables that were related to the nine pillars were considered.

Figure 3-2 illustrates the selection method that was taken. Based on the model developed in Chapter 2, variables were selected from the 300 CIRP variables and some MAIS variables to represent the model's pillars of student success. The initial CIRP database of 300 variables for each cohort year was "filtered" into a smaller database. This smaller database contained the active variables that were considered representative of the model's pillars in the empirical analysis.

3.1.2 Selection Criteria

As I approached these selection criteria, I appreciated the availability of the richness of the questions in the HERI/UCLA CIRP survey. The selection criteria were based on maximizing the selection of variables from the CIRP data that would contribute to my research on freshman engineering success. For each pillar of the model, a set of variables were selected based on the following criteria:

1. Support was found in the literature review presented in Chapter 2. This support could come from either the engineering education literature or the education literature. For example, the high school GPA was selected for P1. High School Academic Achievement. In the literature review, many research studies included the high school GPA as a possible predictor of student academic success and it was found to be significant. The majority of variables fall into this category.

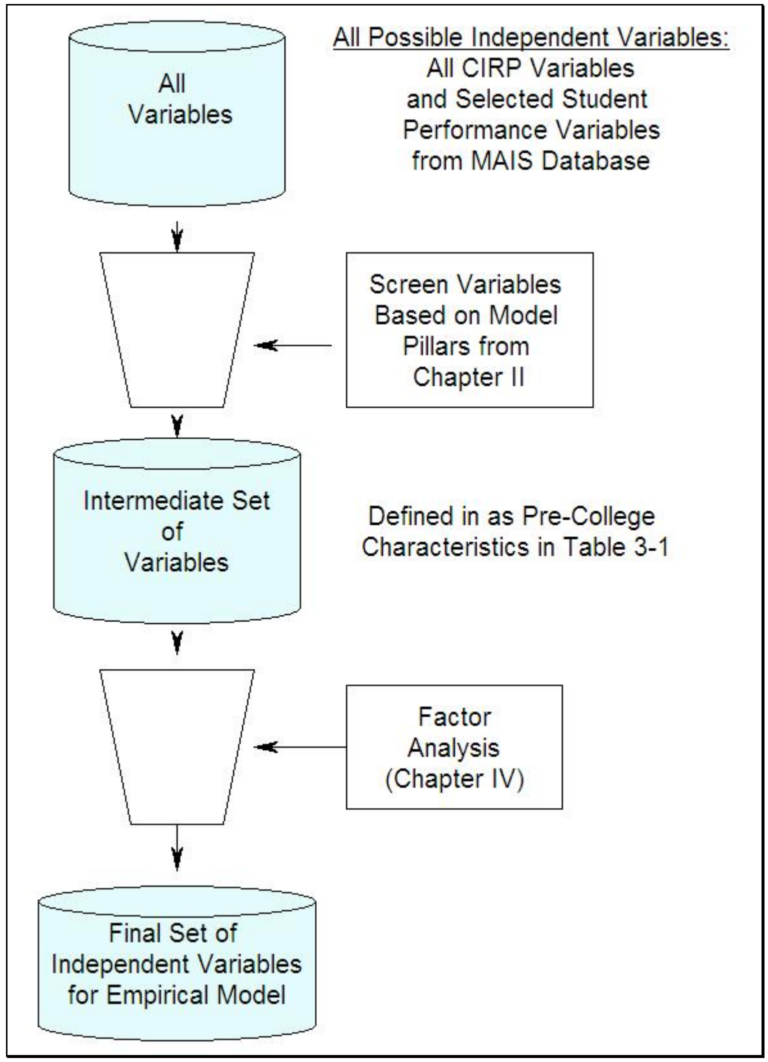

Figure 3-2: Selection and Filtering of the Pre-College Variables

2. If a CIRP variable was considered related to a variable in group 1), it was added to that pillar. For example, there was strong support for self-rating of math ability in the HERI studies, but less support for self-rating of computer ability. This variable was added, as a subjective decision, because I thought it was related to self-rating of math ability.
3. For the Social Engagement pillar, I had some literature review results, but not consistent indicators of social engagement. I reviewed the survey

questions related to social engagement and choose a set of questions, based on both my general readings of the leaders in engineering education and education; and also based on my experience of what makes a successful engineer. I considered this as traditional model-building, in the engineering sense expressed by Box, Hunter, and Hunter (1978). A few variables were selected in this way for the other pillars also, but primarily for the Social Engagement pillar.

4. Because factor analysis works well with continuous variables, all selected variables had an underlying continuum, either continuous or ordinal. Binary variables were not included.
5. At least two variables were selected for each pillar.

In the next section, the rationale for each pillar's variable will be given.

3.2 Pre-College Characteristics

3.2.1 List of Pre-College Characteristics Used as Predictors in Model

Table 3-1 shows the pre-college characteristics included in this study. These include both variables from the HERI / CIRP survey and the MAIS student performance databases. A summary of the averages and standard deviations for both the 2004 and 2005 cohorts is given in Appendix A.

3.2.2 Rationale for Each Pillar's Variables

The rationale for each variable is explained in this section. In most cases, variables were included because there was literature-based evidence. For each pillar, a table is presented that indicates the variables for which literature-based evidence is presented. Chapter 2, Section 2.6.2, contains the literature review explanation. For the variables that were included with no literature based evidence, the Discussion section (associated with each pillar) explains the rationale that was used.

Table 3-1: Pre-College Characteristics by Pillar

P1. High School Academic Achievement
1. High school GPA (corrected for non-significant courses)
2. High school class rank
3. ACT composite*
4. SATI total**
5. Self-rating of academic ability
6. Self-rating of cooperativeness
7. Self-rating of leadership ability
8. Self-rating of writing ability
9. Self-rating of self-confidence (intellectual)
P2. Quantitative Skills
1. ACT math score*
2. SAT math score**
3. ACT science score*
4. UM math placement test score
5. UM chemistry placement test score
P3. Study Habits
1. Hours per week in the past year spent on studying/ doing homework
2. Hours per week in the past year spent talking to teacher outside of class
3. Hours per week in the past year spent reading for pleasure
4. Frequency of using the Internet for research or homework
5. Frequency of studying with other students
6. Frequency of asking a teacher for advice after class
7. Frequency of tutoring another student
8. Frequency of coming late to class
9. Frequency of feeling overwhelmed by all a student had to do
10. Importance in deciding to go to college: to learn more about things that interest me
11. Chance in the future to communicate regularly with your professors
P4. Commitment to Career and Educational Goals
1. Highest academic degree that you intend to obtain
2. Importance in deciding to go to college: to get training for specific career
3. Importance in deciding to go to college: to prepare myself for graduate or professional school
4. Importance in deciding to go to college: to be able to make more money
5. Chance in the future to change major field
6. Chance in the future to change career choice
7. Self-rating on drive to achieve
8. Importance of making a theoretical contribution to science
Note: * indicates characteristic is used in ACT subset only; ** indicates characteristic is used in SAT subset only.

Table 3-1: Pre-College Characteristics by Pillar (continued)

P5. Confidence in Quantitative Skills
1. Self-rating of computer skills
2. Self-rating of mathematical ability
3. Self-rating of creativity
P6. Commitment to this College (U-M)
1. What choice is this college?
2. To how many other colleges other than this one did you apply for admissions?
3. Importance of coming to this college: college has good academic reputation
4. Importance of coming to this college: college has good reputation for social activities
5. Importance of coming to this college: rankings in national magazine
6. Importance of coming to this college: college's graduates get good jobs
7. Importance of coming to this college: my relatives wanted me to come here
8. Importance of coming to this college: offered financial assistance
9. Importance of coming to this college: not offered aid by first choice
10. Chance in future you will be satisfied with this college
P7. Financial Needs
1. Concern about ability to finance college education
2. How much of first year's educational expenses are expected to be from loans?
P8. Family Support
1. Education level of father
2. Education level of mother
P9. Social Engagement
1. Self-confidence (social)
2. Hours per week in past year socializing with friends
3. Hours per week in past year playing video/computer games
4. Hours per week in past year partying
5. Hours per week in past year working (for pay)
6. Hours per week in past year volunteer work
7. Hours per week in past year student clubs/groups
8. Chance in the future you will join a social fraternity or sorority
9. Chance in the future you will play varsity/intercollegiate athletics
10. Chance in the future you will participate in student clubs/groups
11. Chance in the future you will participate in a study abroad program

A summary of the rationale for the variables in each pillar of student success is discussed next.

P1. High School Academic Achievement

The objective of this pillar is to represent with both academic and non-academic characteristics the high school academic achievement prior to college.

Table 3-2: Checklist of Literature Based Evidence for Variables Associated with P1. High School Academic Achievement

Variable	Literature-Based Evidence of Effect
1. High School GPA (corrected for non-significant courses)	Yes
2. High School Class Rank	Yes
3. ACT Composite	Yes
4. SAT Total	Yes
5. Self-Rating of Academic Ability	Yes
6. Self-Rating of Cooperativeness	See Discussion
7. Self-Rating of Leadership Ability	See Discussion
8. Self-Rating of Writing Ability	Yes; See Discussion
9. Self-Rating of self-confidence (intellectual)	Yes

Discussion

In choosing non-academic characteristics for this pillar, I was influenced by the meta-analysis by Lotkowski, et al. (2004), *The Engineer of 2020* and my own experience in working with middle-school and high-school students.

The CIRP variables, self-rating of academic ability and self-rating of self-confidence (intellectual) were selected as being related to academic self-confidence. In asking which variables could fit in this pillar and predict academic success, I hypothesized that a high self-rating of leadership and cooperativeness were important attributes for academic success in a highly selective, highly competitive engineering college. In support, Astin and Astin (2000) discuss the importance of leadership and cooperative skills in college; this concept could be extended to high school studies as a preparation for college. Students who learn leadership and cooperativeness skills in high school tend to be the high achieving students and this contributes to their college success. (In my experience working with youth interested in the STEM disciplines, I learned that leadership and cooperativeness are important attributes for success on STEM-related activities such as

Odyssey of the Mind and Science Olympiad, and the curriculum-related AP courses, all of which are recognized as contributing to successful engineering students.) Both industry and the National Academy of Engineering (*The Engineer of 2020,* (2004*))* have indicated the importance of leadership and cooperativeness (on work teams) as desirable characteristics of entry-level engineers.

Because I was comparing the engineering sector to the Non-STEM sector, I was interested in adding a variable to the overall set of variables that was comparable to self-rating of math (in P5-Confidence in Quantitative Skills) for the Non-STEM sector. I decided to add self-rating of writing skills. My rationale was that the Non-STEM sector includes humanities and social studies majors who take courses that require significant writing. Besterfield-Sacre et al. (1997) found self-rating of writing and speaking skills to be a significant predictor for attrition. Hawley and Harris (2005-2006), in a retention study of a community college, found self-rating of writing to be significant in their factor analysis. I added it to this pillar because I considered it to be highly related to high school academic achievement. Either a factor analysis or regression analysis would indicate the final significance of this variable. In addition, its selection made it available for analyses for the Non-STEM student sector.

P2. Quantitative Skills

The objective of this pillar is to present the quantitative and analytical skills in high school of the entering college students.

Table 3-3: Checklist of Literature Based Evidence for Variables Associated with P2. Quantitative Skills

Variable	Literature-Based Evidence of Effect
1. ACT Math Score	Yes
2. SAT Math Score	Yes
3. ACT Science Score	See Discussion
4. UM Math Placement Test Score	See Discussion
5. UM Chemistry Placement Test Score	See Discussion

Discussion

Budny et al. (1998) discussed the importance of correct placement into the freshman level courses for student academic success and retention. The literature review for engineering retention studies consistently showed that the SAT math and ACT math scores are predictors of both academic success and retention. (See Section 2.6.2, P2. Quantitative Skills.) Veenstra and Herrin (2006a) found that the ACT Math score of 27 was a predictor of earning a passing grade in the Calculus I, Chemistry, and Engineering 100 and Engineering 101 at Michigan. The ACT Science score measures scientific reasoning; this is an important basis for strong analytical skills, which are needed for engineering (NAE, 2004). Unpublished reports at the University of Michigan have shown that the SAT Math, ACT Math, ACT Science, and placement tests are predictors of academic success in individual courses or related to the first year GPA. The University of Michigan (UM) Math Placement Test Score is part of the placement criterion for placement into either Pre-Calculus or Calculus I. It tests incoming students on their knowledge of pre-calculus. The UM Chemistry Placement Test Score is used to determine if a student needs an extra lecture session per week in the Chemistry I course. It tests incoming freshmen on their scientific reasoning and knowledge of high school chemistry.

P3. Study Habits

The objective of this pillar is to represent the study habits that were learned in high school.

Discussion

The literature review supports the significance of being an independent learner as important for engineering student success. In Tinto's model of social and academic integration, he explains that this leads to learning, and learning is needed to be successful in college (Tinto, 1993). He wrote, "The more students learn, the more value they find in their learning, the more likely they are to stay and graduate" (Tinto, 2005). Astin and Astin explained that the learning environment is enhanced by a "collaborative learning environment". They further explained that:

a new paradigm is emerging that "embraces both students and faculty as teachers and learners. In this new paradigm, "students are expected to engage each other and their professors actively in a dynamic learning environment" (Astin and Astin, 2000).

Table 3-4: Checklist of Literature Based Evidence for Variables Associated with P3. Study Habits

Variable	Literature-Based Evidence of Effect
1. Hours per week in the past year spent on Studying/ doing Homework	Yes
2. Hours per week in the past year spent Talking to teacher outside of class	Yes
3. Hours per week in the past year spent Reading for pleasure	See Discussion
4. Frequency of using the Internet for research or homework	See Discussion
5. Frequency of studying with other students	Yes
6. Frequency of asking a teacher for advice after class	Yes
7. Frequency of tutoring another student	See Discussion
8. Frequency of coming late to class	Yes
9. Frequency of feeling overwhelmed by all a student had to do	Yes
10 Importance in deciding to go to college: "to learn more about things that interest me"	See Discussion
11.Chance in the future to communicate regularly with your professors	See Discussion

In support of both Tinto and the Astins' ideas on learning, CIRP variables were chosen that 1) suggest learning through collaborative learning of the high school student with teachers and other students and 2) suggest the student's expectation of continuing this style of collaborative learning in college. Although some of these variables could be considered as social engagement variables, they were placed in P3 (Study Habits) because these activities were considered directly related to study habits and learning.

"Frequency of using the Internet for research or homework" was selected because many students in high school use the Internet for research, especially in the honors and AP courses. It is consistent with the ideas of learning to be an independent learner. With respect to "Chance in the future to communicate regularly with your professors", I hypothesized that if a student spent time talking to teachers in high school, they would be more inclined to talk to professors and this would improve academic success. This is consistent with Tinto's integration concepts and the Astins' collaborative learning as discussed above. Frequency of studying with other students, and Frequency of tutoring another student in high school are questions that are consistent with Tinto's integration concepts and the Astins' collaborative learning as discussed above. The importance in deciding to go to college: "to learn more about things that interest me" is consistent with being an independent learner and has potential as a significant predictor. Likewise, Hours per week reading for pleasure was seen as an indication of an independent learner.

P4. Commitment to Career and Educational Goals

The objective of this pillar is to represent the variables related to commitment to career and educational goals.

Discussion

All were selected based on evidence from the literature review.

Table 3- 5: Checklist of Literature Based Evidence for Variables Associated with P4. Commitment to Career and Educational Goals

Variable	Literature-Based Evidence of Effect
1. Highest Academic Degree that you intend to obtain. *	Yes
2. Importance in deciding to go to college: "to get training for specific career"	Yes, for engineering
3. Importance in deciding to go to college: "To prepare myself for graduate or professional School"	Yes
4. Importance in deciding to go to college: " To be able to make more money"	Yes
5. Chance in the future to change major field	Yes
6. Chance in the future to Change Career Choice	Yes
7. Self-Rating on Drive to Achieve	Yes
8. Importance of Making a theoretical contribution to science	Yes

*This variable was recoded to: 0=None, 1= Associate degree or less, 2= Bachelor's degree 3= Masters Degree including M.DVD and 4= PhD, Ed.D, M.D., D.O.,DDS, DVM, JD.

P5. Confidence in Quantitative Skills

The objective of this pillar is to represent the confidence in quantitative skills. Strong support for this exists in the engineering education literature.

Table 3-6: Checklist of Literature Based Evidence for Variables Associated with P5. Confidence in Quantitative Skills

Variable	Literature-Based Evidence of Effect
1. Self-Rating of Computer Skills	See Discussion
2. Self-Rating of Mathematical Ability	Yes
3. Self-Rating of Creativity	See Discussion

Discussion

Self-rating of computer skills was considered to be related to self-rating of math ability for which there is literature support. I was influenced by *The Engineer of 2020* (NAE, 2004) to add "self-rating of creativity". I wanted this variable to be available for modeling of student academic success and retention. From my experience as an engineer and reading of *The Engineer of 2020*, I recognized that engineers will need creativity (which is a component of innovative thinking). This variable was probably the most difficult to place in one of the pillar groups. I felt that self-rating of creativity does lead to a higher level of confidence in engineering skills, of which confidence in quantitative skills is a component. If it was not important, it would not enter into either the factor analysis or regression analysis.

P6. Commitment to this College

The objective of this pillar was to represent variables related to motivation to attend Michigan because it was the first choice college and to capture the reasons for attending Michigan. There was strong support in the education research literature, but not in the engineering education literature.

Discussion

There was evidence in the literature supporting the choice of the college. The CIRP question "To how many other colleges other than this one did you apply for admissions?" was seen as related to choice; the more colleges, the less the certainty of a choice. The CIRP survey has a series of questions on the importance to the student of attending this college. (Very important, somewhat important, not important). Seven questions from this series were included in the set of variables and they were all assigned to this pillar, Commitment to this college. They indicate the strength of the reason for attending this college. The CIRP question "Chance in future you will be satisfied with this college" was chosen because of its orientation toward quality of expected experience; it also is related to the strength of a college choice. If a student expects to be satisfied, the commitment to that college is intrinsically stronger with an assumed higher probability of retention.

Table 3-7: Checklist of Literature Based Evidence for Variables Associated with P6. Commitment to this College

Variable	Literature-Based Evidence of Effect
1. What Choice is this college?	Yes
2. To how many other colleges other than this one did you apply for admissions?	See Discussion
3. Importance of coming to this college: College has good academic reputation	See Discussion
4. Importance of coming to this college College has good reputation for social activities	See Discussion
5. Importance of coming to this college Rankings in national magazine	See Discussion
6. Importance of coming to this college College's graduates get good jobs	See Discussion
7. Importance of coming to this college: My relatives wanted me to come here	See Discussion
8. Importance of coming to this college Offered financial assistance	See Discussion
9. Importance of coming to this college: Not offered aid by first choice	See Discussion
10.Chance in future you will be satisfied with this college	See Discussion

P7. Financial Needs

The objective of this pillar was to represent variables related to the financial needs of students.

Table 3-8: **Checklist of Literature Based Evidence for Variables Associated with P7. Financial Needs**

Variable	Literature-Based Evidence of Effect
1. Concern about ability to finance college education	Yes See Discussion
2. How much of first year's educational expenses are expected to be from loans?	Yes

Discussion

With the rising costs of college attendance, significant literature exists on the need for financial help for higher student retention. Related to the two questions selected from the CIRP survey, there is less evidence of the importance of the question, “Do you have any concern about ability to fianace your college education” with responses being none, some or major. I liked this question because it was an affective question on the concern the student had about his/her finances for college. With the three levels of responses, it could be used to identify differences between students with major concern about finances and minor or no concern.

P8. Family Support

Initially, the objective of this pillar was to represent the support that the extended family gives to a college student.

Table 3-9: Checklist of Literature Based Evidence for Variables Associated with P8. Family Support

Variable	Literature-Based Evidence of Effect
Parents’ Education	Yes

Discussion

More evidence supports the need for the continuing support of the family in helping a student adjust to college. The best available variable to represent this was the education level of the parents. If parents have a high level of education, they will encourage their children to attend college and complete a degreed program. I did not include financial information about parents in this category for two reasons: 1) to the CIRP question of “what is your best estimate of your patents’ total income last year”, there was much missing data and 2) in the Astin and Oseguera (2005) study, education level of the parents was significant for retention, but income level was not consistently significant.

The two CIRP variables: Education Level of Father and Education Level of Mother were combined to indicate the overall education level of both the mother's and father's education (as a family unit) as follows:

Parents' Education = Max (Mother's Education code, Father's Education code)

The coding of Parents' Education was revised to:

1= less than high school

2= High school graduate

3= some college or postsecondary education

4=College degree (Bachelor)

5= Graduate school or Graduate degree

P9. Social Engagement

The objective of this pillar was to represent Astin's theory of involvement, i.e. the more involved students are in social activities relate to their college, the more they learn.

Discussion

The literature was varied on support for individual questions. Questions were chosen that I thought supported Astin's theory of involvement. The Lotkowski et al. (2004) study showed general support for the importance of social engagement (social involvement in their report) for both academic success and retention across 109 retention studies. In addition, the question: Chance in the future you will participate in a study abroad program was added because of the importance that the engineering community attached to being an engineer in the global community in *The Engineer of 2020* (NAS, 2004). Nicholls et al. (2007) found a significant difference between STEM and Non-STEM students for this variable.

Table 3-10: Checklist of Literature Based Evidence for Variables Associated with P9. Social Engagement

Variable	Literature-Based Evidence of Effect
1. Self-Confidence (social)	Yes
2. Hours per week in past year-socializing with friends	Yes
3. Hours per week in past year- playing video/computer games	Yes
4. Hours per week in past year-partying	Yes
5. Hours per week in past year-working (for pay)	Yes
6. Hours per week in past year-volunteer work	Yes
7. Hours per week in past year-student clubs/groups	Yes
8. Chance in the future you will join a social Fraternity or sorority	Yes
9. Chance in the future you will play varsity/Intercollegiate athletics	Yes
10. Chance in the future you will participate in student clubs/groups	Yes
11. Chance in the future you will participate in a study abroad program	See Discussion

3.3 Calculations of Dependent Variables (Model Output)

The calculations of the four academic success and retention variables, which serve as the dependent variables in the empirical model are discussed in this section:

1. 1st year GPA.
2. 1st year STEM GPA, a GPA based on the science, math and engineering courses taken in the freshman year.
3. Retention status in the admitting College. Whether a student was still in the same College at the beginning of the fall term of his/her 2nd year.
4. Retention Status with respect to the University. Whether a student was still enrolled in the university at the beginning of the fall term of his/her 2nd year.

The variables originated from the MAIS data system.

3.3.1 First Year GPA

The first year GPA is defined as the Grade Point Average (GPA) for all courses in which the student completed in his/her first year of college.

It was calculated from the freshman fall term number of credits and term GPA; and the winter term number of credits and term GPA. It is illustrated with the variable names used in the database:

- Term1un – Number of credit hours taken in the fall term that go into the fall term GPA. Does not include credits taken for pass/fail credit
- Term1gpa- Fall term GPA
- Term2un – Number of credit hours taken in the winter term that go into the winter term GPA. Does not include credits taken for pass/fail credit.
- Term2gpa- Winter term GPA

The first year GPA was then calculated as:

$$1^{st}\text{ Year GPA} = (\text{Term1un*Term1gpa+Term2un*Term2gap})/(\text{Term1un+Term2un})$$

If a student withdrew in the first term, the first year GPA was not calculated.. If a student withdrew or did not register in the 2^{nd} term, only the first term GPA was used in the calculation.

3.3.2 First Year STEM GPA

First year STEM GPA is defined as the weighted average of the grades of 100- level STEM courses taken in the freshman year.

Table 3-11 lists the 100-level STEM courses and the number of credits associated with each course. The grades, which are available in MAIS database as letter grades, were converted to a numeric course GPA, based on a 4-point scale. The STEM GPA was then calculated as the weighted average of the numeric course GPA, weighted by the course credit hours.

$$\text{First Year STEM GPA} = \sum (HR_i \text{ X Course } GPA_i) / \sum (HR_i)$$

In order to have an equitable comparison between different STEM majors, only 100-level courses are included in this calculation. (Some students test with AP scores into 200-level course.) Engineering 110 is not included in the STEM GPA; it is a survey course on engineering careers.

TABLE 3-11: STEM Courses and Credit Hours

Course Number and Name	Number of Credit Hours
BIOLOGY 162-Introductory Biology	5
CHEM 125- General Chemistry Laboratory I	1
CHEM 126-General Chemistry Laboratory II	1
CHEM 130-General Chemistry and Reaction Principles	3
ENGR 100-Introduction to Engineering	4
ENGR 101-Introduction to Computers and Programming	4
MATH 105-Data, Functions and Graphs	4
MATH 110-Pre-Calculus	2
MATH 115-Calculus I	4
MATH 116-Calculus II	4
MATH 156-Applied Honors Calculus II	4
MATH 185-Honors Calculus I	4
PHYSICS 125-General Physics Mechanics and Sound	4
PHYSICS 126-Electricity-Light	4
PHYSICS 127-Mechanics and Sound Lab	1
PHYSICS 140-General Physics I for Scientists and Engineers	4
PHYSICS 141-Elementary Lab I	1
PHYSICS 160-Honors Physics I	4

3.3.3 Calculation of Student Retention

The definitions of College Retention and University Retention are defined in this section. Only full-time freshmen enrolling for the first time in the summer or fall of the freshman class year are included.

Definition of College Retention

For a particular college, College Retention is the percent of students who enrolled in that college in the fall term of the freshman year and are registered in the same college at the beginning of classes for the third term (fall term 2nd year).

Definition of University Retention

University Retention is the percent of students who enrolled in a college in the fall term of the freshman year and are registered in any college of the university at the beginning of classes for the third term. (i.e. some may have transferred to another college within the university.)

Students who enrolled in courses past the first day of courses in the third semester (fall) and then withdrew from the university were considered to be retained.

3.4 Student Sectors

The thesis is that the modeling of engineering academic success and retention is different from other student sectors. To support this, one of the research objectives of this Ph.D. research was to compare Engineering students' performance to three other student sectors:

- Pre-Med Students (an identified pre-professional sector with a high level of scientific knowledge)
- STEM Students (excluding engineering and Pre-Med in order to have independent samples). STEM students generally include Science, Technology, Engineering and Math majors.
- Non-STEM students

One of the challenges of this research was to define each sector. A preliminary literature review showed that a common definition of "STEM" majors does not exist in the U.S. This section defines the student sectors, as it was used in this research.

For the Engineering student sector, all students registered in the College of Engineering were considered as Engineering students. For the Pre-Med student sector, all students with a CIRP variable of student's probable career of Physician were considered in this sector. The CIRP variable, student's probable major was used to determine if the remainder of the students could be classified as STEM or Non-STEM students. There were a few "probable major" categories that still were difficult to determine. I exchanged emails with Gillian Nicholls of the University of Pittsburgh, who has researched the history of the definitions of STEM and their inconsistencies (Nicholls, 2007a, Nicholls, et al., 2007). Her dissertation chapter on this subject was reviewed and used in identifying if a major was a STEM or Non-STEM major (Nicholls, 2007b). If the "student's probable major" code was "undecided" or not specific enough to make this determination, the student's sector was considered to be missing data. More detail is given below.

3.4.1 Definitions of each Student Sector

Engineering Sector (Student Sector Code =1)

All Engineering majors in the College of Engineering. (LSA has a few students with probable major of engineering; they were categorized as Science and Math (STM) majors)

Pre-Med Sector (Student Sector Code=2)

All students who indicated a Probable Career as Physician were included in this student sector, regardless of college. The only exception to this coding was that Engineering students who indicated a probable career as a physician were categorized as belonging to Engineering. In this research, Pre-Med majors were selected as an example of a pre-professional program. Michigan does not have a formal Pre-Med program; as a result a range of majors are included.

STM Sector - STEM Majors Excluding Engineering and Pre-Med (Student Sector Code=3)

This student sector is denoted as the STM sector, since it does not include Engineering. The Majors in the STM sector include: All Science, math, technology, medical or healthcare technology, forestry, architecture and urban planning.

Non-STEM Sector- Non-STEM Majors (Student Sector Code=4)

The following majors are included: art and humanities, social science, business, education, kinesiology and therapy

3.4.2 Description of Table 3-12

A more detailed listing is shown in the Table 3-12. A "probable major" code is not coded (indicated as "missing") if:

- There is insufficient information in the name of the CIRP "probable major" code to make this determination. This would apply to code 60-Other Professional or 85-Undecided.
- The University of Michigan does not have a degree in this area. For example, the University of Michigan would not have a degreed program in the building trades (this is usually an associate degree).

For some majors, the freshman curriculum at Michigan was reviewed to decide it was more appropriately classified as a STEM or Non-STEM major in terms of freshman retention. For example, Architecture and Urban Planning was categorized as a STEM discipline. It is a major in the School of Arts (usually a Non-STEM field) and its students are required to take Calculus I (Math 115) and Physics. For this reason, it was categorized as a STEM major. Forestry was considered as a major field in Environmental Sciences, which requires all students to take two semester of Calculus. Based on this, Forestry was categorized as a STEM discipline.

Approximately 10% of the students were undecided about their major and were not assigned a student sector code.

TABLE 3-12: Coding for STM and Non-STEM Student Sectors Based on the CIRP "Student's Probable Major"

CIRP Student's Probable Major Numeric Code and Label[4]	STM or Non-STEM	CIRP Student's Probable Major Numeric Code and Label	STM or Non-STEM
Arts and Humanities		**Business**	
1= Art, fine or applied	Non-STEM	20=Accounting	Non-STEM
2=English (language and literature)	Non-STEM	21=Business Administration (general)	Non-STEM
3=History	Non-STEM	22=Finances	Non-STEM
4=Journalism	Non-STEM	23=International Business	Non-STEM
5=Language and Literature (except English)	Non-STEM	24=Marketing	Non-STEM
6=Music	Non-STEM	25=Management	Non-STEM
7=Philosophy	Non-STEM	26=Secretarial Studies	Non-STEM
8=Speech	Non-STEM	27=Other Business	Non-STEM
9=Theater or Drama	Non-STEM	**Education**	
10=Theology or Religion	Non-STEM	28=Business Education	Non-STEM
11=Other Arts and Humanities	Non-STEM	29=Elementary Education	Non-STEM
Biological Sciences		30=Music or Art Education	Non-STEM
12=Biology(general)	STM	31=Physical Education or Recreation	Non-STEM
13=Biochemistry or Biophysics	STM	32=Secondary Education	Non-STEM
14=Botany	STM	33=Special Ed.	Non-STEM
15=Environmental Science	STM	34=Other Education	Non-STEM
16=Marine(Life) Sciences	STM		
17=Microbiology or Bacteriology	STM		
18=Zoology	STM		
19=Other Biological Sciences	STM		

[4] CIRP Student Probable Major are from: the CIRP 2005 Freshman Survey Data File (File Documentation), File Name: CIRP2005.DAT, from the Higher Education Research Institute, UCLA

TABLE 3-12: Coding for STM and Non-STEM Student Sectors Based on the CIRP "Student's Probable Major" (continued)

CIRP Student's Probable Major Numeric Code and Label	STM or Non-STEM	CIRP Student's Probable Major Numeric Code and Label	STM or Non-STEM
Engineering		**Professional (cont.)**	
35=Aeronautical Engineering	STM	54=Health Technology (medical, dental, laboratory)	STM
36=Civil Engineering	STM	55=Library or Archival Science	Non-STEM
37=Chemical Engineering	STM	56=Medicine, Dentistry, Veterinary Medicine	STM
38=Computer Engineering	STM	57=Nursing	STM
39=Electrical or Electronic Engineering	STM	58=Pharmacy	STM
40=Industrial Engineering	STM	59=Therapy (occupational, Physical, speech)	Non-STEM
41=Mechanical Engineering	STM	60=Other Professional	Non-STEM
42=Other Engineering	STM	**Social Sciences**	Non-STEM
Physical Sciences and Math	STM	61=Anthropology	Non-STEM
43=Astronomy	STM	62=Economics	Non-STEM
44=Atmospheric Science (including Meteorology)	STM	63=Ethnic Studies	Non-STEM
45=Chemistry	STM	64=Geography	Non-STEM
46=Earth Science	STM	65=Political Science (gov't., international relations)	Non-STEM
Professional		66=Psychology	Non-STEM
47=Marine Science (incl. Oceanography)	STM	67=Social Work	Non-STEM
48=Mathematics	STM	68=Sociology	Non-STEM
49=Physics	STM	69=Women's Studies	Non-STEM
50=Statistics	STM	70=Other Social Studies	Non-STEM
51=Other Physical Sciences	STM	**Technical**	
52=Architecture and Urban Planning	STM	71=Building Trades	missing
53=Family and Consumer Sciences	Non-STEM	72=Data Processing or Computer Programming	STM
		73=Drafting or Design	STM
		74=Electronics	STM

TABLE 3-12: Coding for STEM and Non-STEM Student Sectors Based on the CIRP "Student's Probable Major" (continued)

CIRP Student's Probable Major Numeric Code and Label	**STM(STEM) or Non-STEM**
Technical (cont.)	
75=Mechanics	STM
76=Other Technical	missing
Other Fields	
77=Agriculture	STM
78=Communications	Non-STEM
79=Computer Science	STM
80=Forestry	STM
81=Kinesiology	Non-STEM
82=Law Enforcement	Non-STEM
83=Military Science	Non-STEM
84=Other Field	missing
85=Undecided	missing

3.5 IRB Approval Database Requirements

IRB approval was received from the University of Michigan IRB board for this research. The IRB study number and title is HUM00007149 Research on First Year Engineering Student Success and Retention for 2003, 2004 and 2005 freshmen classes. In the IRB application, three sources of data were defined:

1) The UCLA/ Higher Education Research Institute (HERI) Cooperative Institutional Research Program (CIRP) survey. The CIRP survey is a national survey that has been conducted for the past 40 years by UCLA. The CIRP survey includes questions on 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. During freshman orientation, all freshmen were invited to participate in the CIRP survey; this survey is administered by Division of Student Affairs Office at the University of Michigan.
2) Data on student performance including ACT/SAT component scores, placement scores, number of credit units, term GPA and grades for freshman STEM courses.

This data is collected from the Michigan Administrative Information Services (MAIS) database.

3) Student support data from the College of Engineering including frequency of advising and whether a student participated in a mentoring program.

These databases were merged for the 2004 and 2005 freshman class cohorts (fall 2004 and fall 2005). Note that initially the 2003 database was to be included in the analysis. Because of a low response rate, it was not considered

IRB approval for the research required that the databases be merged without my having access to any personal identifiers. Among the three databases, the only common variables that could be used as a merge index variable was the student ID. The actual merging of the databases was coordinated through the efforts of the Division of Student Affairs Office and the Registrar's Office. Part of the process included identifying students who had given permission for their CIRP survey data to be used in research projects. After these records were selected, a verification of students who were full-time, first-time freshmen was conducted. After a database was created consistent with the IRB plan, the student ID and personal identifiers were deleted. This new database was then delivered to me for further data processing as described in this chapter.

3.6 Response Rates and Permission Rates for the CIRP Survey

The response rates for the CIRP survey for these two freshman classes (2004 and 2005) were 75% for both 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% for 2004 and 33% for 2005. A review of the sample rate by gender and ethnicity showed good representation in all areas; an inherent sampling bias was detected. The overall response rate (including the survey and permission rate) for the 2004 and 2005 cohorts are shown in Tables 3-13 and 3-14.

Review of Table 3-13 and 3-14 show a very consistent response rate across all colleges for the 2004 cohort with the exception of a low response rate for Kinesiology. For the

2005 cohort, the response rates for the LSA, Engineering and Nursing colleges were highest. For both cohorts, there was good participation in the CIRP survey by gender and race. The participation of international students in the 2004 cohort in both Engineering and LSA was substantially less than expected (2% and 8% respectively). For the 2005 cohort, participation by engineering international students was only 7% compared to 27% for LSA students.

Table 3-13: Response Rates for the CIRP Survey 2004 and 2005 Cohorts, Overall and for the College of Engineering

	Freshmen Population 2004	CIRP Survey Sample 2004	Response Rate (%) 2004	Freshmen Population 2005	CIRP Survey Sample 2005	Response Rate (%) 2005
Overall	6040	1650	27%	6115	2010	33%
Engineering	1290	336	26%	1206	399	33%
LSA	4178	1176	28%	4353	1450	33%
Other Colleges						
Art and Design	99	24	24%	106	27	25%
Kinesiology	178	28	16%	163	43	26%
Music	189	55	29%	181	49	27%
Nursing	106	31	29%	106	42	40%
College of Engineering						
Gender						
Female	324	81	25%	300	112	37%
Male	966	250	26%	906	285	31%
Race						
Asian	181	56	31%	189	55	29%
Black	51	14	27%	52	16	31%
Hispanic	45	15	33%	41	12	29%
White	739	217	29%	783	293	37%
International Students	150	3	2%	98	7	7%

Table 3-14: Response Rates for the CIRP Survey 2004 and 2005 Cohorts, College of LSA

	Freshmen Population 2004	CIRP Survey Sample 2004	Response Rate (%) 2004	Freshmen Population 2005	CIRP Survey Sample 2005	Response Rate (%) 2005
College of LSA						
Gender						
Female	2367	705	30%	2457	882	36%
Male	1811	464	26%	1896	564	30%
Race						
Asian	505	137	27%	562	163	29%
Black	271	46	17%	342	85	25%
Hispanic	200	49	25%	242	70	29%
Nat. Amr.	44	10	23%	52	16	31%
White	2681	859	32%	2850	1042	37%
International students	144	11	8%	131	36	27%

3.7 Databases

For reference, this section was added to discuss the databases used for each analysis in this dissertation. As the chapters are discussed, more detail about the data used in each analysis will be discussed.

3.7.1 Discussion of Database Structure

Based on the analyses being used, different subsets of the data were used. A summary of the databases is presented in Table 3-15. This paragraph summarizes some of the key issues that led to the different databases. The Filtered Database and Factor Analysis Database were for the preparation of the data. The 2004 ACT Regression, and 2004 SAT Regression Databases were used for the initial modeling of academic success. The 2005 ACT Cross-Confirmation and SAT Cross- Confirmation were used for cross-validation of the predictions from the 2004 cohort predictions. The Retention database included the combined 2004 and 2005 database and was use to predict student retention. The Randomized Database was a special application for the study of interventions.

Table 3-15: Description of Databases

Database	Analysis	N	Comments
Filtered Database For both the 2004 and 2005 cohort	Input to Factor Analysis	3660	Contains the selected variables for the pillars of student success (Table 3-1) and calculated output Variables discussed in this chapter
Factor Analysis	Factor Scores (Chapter IV)	3660	Contains the variables for the pillars of student Success (Table 3-1), factor scores, and output variables for both the 2004 and 2005 cohorts. Used for the contribution of each pillar in Chapter V. Missing data was controlled within each pillar with the listwise missing data option.
2004 ACT Regression	Regression For Academic success (1^{st} year GPA) (Chapter V & VII)	635	Contains the factor scores for the 2004 cohort (all student sectors) with no missing data among the factor scores and model output variables. Includes only students who reported their ACT scores and had no missing data among the ACT test scores.
2004 SAT Regression	Regression For Academic success (1^{st} year GPA) (Chapter V & VII)	608	Contains the factor scores for the 2004 cohort (all student sectors) with no missing data among the factor scores. Includes only students who reported their SAT scores and had no missing data among the SAT test scores.
2005 ACT Cross-Confirmation Engineering Sector	Cross-confirmation for model of academic success (Chapter V)	161	Contains the factor scores from the 2005 cohort (with no missing data) and model output variables. Includes only students who reported their ACT scores and had no missing data among the ACT test scores. (Engineering sector only)
2005 SAT Cross-Confirmation Engineering Sector	Cross-confirmation for model of academic success (Chapter V)	150	Contains the factor scores from the 2005 cohort (with no missing data) and model output variables. Includes only students who reported their ACT scores and had no missing data among the ACT test scores. (Engineering sector only)
Retention Database	Analysis of retention model (Chapters VI and VII)	735	2004 and 2005 cohorts were combined into one database. Due to missing data issues, initial variables in the pillars were used, not the factor scores
Randomized Database	Analysis of effect of engineering Interventions (Chapter V)	27	Sampling of Retention Database for selected variables (both cohorts)

3.7.2 Research Using ACT AND SAT Subsets

Most engineering retention studies use the SAT math and SATI Total in their prediction models of academic success or retention. Only a few studies show that the ACT Math test score is an excellent indicator of student success (Moller-Wong and Eide, 1997; Leuwerke, et al., 2004). In my pre-dissertation PhD research, I conducted an analysis that showed that the ACT Math was a more effective predictor of Calculus I and freshman Chemistry than the SAT Math, using a 2 x 2 contingency table analysis. (Veenstra and Herrin, 2006a) It was hypothesized that this was due to the differences between the ACT Math and SAT Math tests. The ACT Math tested for competence in trigonometry and some pre-calculus while the SAT Math tested for competence only through Algebra II. In addition, the ACT test is of interest because it has a Science Reasoning test, which will be referred to as the ACT Science test. The SAT does not have a science component in standard SAT test (often referred to as the SATI test).

This research project was seen as an opportunity to further compare the effectiveness as a predictor of the ACT Math score compared to the SAT Math score. At Michigan, student can report either the SAT or ACT scores or both for admission consideration. As a result, both the ACT and SAT variables were introduced into the database. In the empirical analysis, two subsets of the database were developed:

1.) Records that included the ACT scores
2.) Records that included the SAT scores.

If a student took both the ACT and SAT, he/she would be included in both subsets. Both subsets would contain all the high school achievement variables such as the high school GPA and Rank and all the CIRP variables. The ACT and SAT subsets affect only the P1 (High School Academic Achievement and P2 (Quantitative Skills) variables. If a student only took the ACT test, he/she would have missing data for the SAT test variables; the same is true for students who took only the SAT test.

A comparison of the ACT and SAT statistics in the survey sample is shown in Table 3-16. It shows a good representation of both the ACT and SAT tests. For the 2004 cohort, 64% of the students reported the SAT test scores and 76% of the students reported the ACT test scores. 40% of the students reported both the ACT and SAT test scores. (See Table 3-16.) Similarly, for the 2005 cohort, 60% of the students reported the SAT test scores and 79% reported the ACT test scores.

Table 3-16: Comparison of Survey Sample Cohorts to Freshman Class for ACT and SAT Statistics

Statistic	2004 Class	2004 Survey Sample	2005 Class	2005 Survey Sample
Number of Freshmen	6040	1650	6115	2010
50% Mid-Range SAT Math	630-720	620-710	630-730	630-720
50% Mid-Range SAT Verbal	580-680	580-690	590-690	600-690
ACT Composite	26-30	27-31	26-31	27-31
Percent with SAT scores	58%	64%	55%	60%
Percent with ACT scores	67%	76%	66%	79%

3.8 Summary

In this chapter, the following were discussed:

- The process for choosing variables for the empirical analysis and the rationale for each variable
- Calculation of the output variables from the model
- Definition of each student sector: Engineering, Pre-Med, STM and Non-STEM
- IRB Approval and response rates from the CIRP survey
- Database Structure, and the definition of the ACT and SAT Subsets

CHAPTER IV
FACTOR ANALYSIS

In Chapter III, the development of the empirical database was discussed. The modeling of academic success using regression analysis (Chapter V) was a challenge with sixty-one predictor variables and multi-collinearity among these predictor variables. Factor analysis was used to reduce the number of predictor variables, reduce the multi-collinearity among the predictor variables, and better understand the underlying latent correlation structure of the variables within a pillar. A factor analysis was conducted on each pillar discussed in Chapters II and III. A strength of factor analysis was that the factors within a pillar were uncorrelated.

Factor analysis is an extension of Principal Component Analysis (PCA). Whereas PCA identifies components that explain most of the total variation among the variables, factor analysis identifies unobserved variables known as latent factors that explain the common variation among the original variables. Factor analysis explores the correlation structure, identifying the set of variables that have a high correlation among themselves, but low correlation with other variables. This set of highly correlated variables will become a factor. Principal Axis Factoring (PAF) is a form of factor analysis and is commonly used in education research studies. PAF was the factor analysis method used for this research.

The theory of eigenvalues, on which PAF is based, and the algorithm used to analyze this data will be presented in Section 4.1 Methodology. Section 4.2 discusses the algorithm of factor analysis for the empirical data and the examination of deleted variables from the factor analysis.. The results from the factor analysis are discussed in Section 4.3. The discussion and summary sections follows in Sections 4.4 and 4.5. As a result of the factor analysis, the sixty-one predictor variables (from the model's nine pillars) were partitioned into nineteen factors. These nineteen factors will be considered as the predictor variables for the regression on academic success in Chapter V.

4.1 Methodology

Both PCA and factor analysis are based on the eigenstructure of the data. The eigenvectors are uncorrelated, resolving the multi-collinearity problem that typically exists among the original variables. Both Principal Components and Factor Analysis assume that the data is distributed as a multivariate normal distribution and that for each variable there is an underlying continuum of either interval or continuous data. (Marques, de Sá, 2003, Johnson and Wichern, 1998)

4.1.1 Eigenvalue Structure

The eigenvalue structure is common to both the theory of PCA and factor analysis. Suppose each freshman has p pre-college characteristics, X_{ij}, where i represents the ith pre-college characteristic (i = 1 to P) and j represents the jth student (j= 1 to N) . Because of a different scale among the X variables in the research data, the correlation matrix was used for explaining both PCA and PAF. Let **R** represent the Pearson correlation matrix of X, the matrix of pre-college characteristics.

The eigenvalue structure of the **R** is defined as:

$$(\mathbf{R} - \lambda_i \mathbf{I})\, \mathbf{e_i} = \mathbf{0} \qquad 4.1$$

where **R** is the correlation matrix of **X**, λ_i is the ith eigenvalue of **R, I** is the identity matrix (pxp) and **e** is the eigenvector (column vector px1) corresponding to the ith eigenvalue. The eigenvectors will define a linear combination of the original variables that explains a higher percent of the total variation of **X.**

To obtain non-trivial solutions of the eigenvectors (equation 4.1), λ_i must be chosen to solve the determinant:

$$|\mathbf{R} - \boldsymbol{\lambda}\mathbf{I}| = 0 \qquad 4.2$$

After solving the determinant for $\boldsymbol{\lambda}$, the eigenvectors can be solved using equation 4.1. The principal components are the eigenvectors, $\mathbf{e}_i$.

The principal components scores for each set of x-values can then be expressed as **Y**

$$\mathbf{Y} = \mathbf{e}' \mathbf{Z} \qquad 4.3$$

where **Z** is the standardized scores of the **X** matrix. Because the eigenstructure is calculated for **R,** the principal component scores are based on the standardized **X** values.

Selecting the Number of Principal Components

The PCA generates p principal components. If all p principal components are used, the dimensionality is the same as the set of variables. The first principal component explains the most variation and the variance of the first principal component is denoted as λ_1. The second principal component will explain the next highest amount of variance with the last principal component explaining the least amount of variance. The variance of the ith principal component is equal to its eigenvalue:

$$\mathrm{Var}(Y_i) = \lambda_i .$$

Because the correlation matrix was used, the total population variance of all principal components is p, the number of original variables. The proportion of variance due to the ith principal component is λ_i / p .

To use PCA to reduce the dimensionality, the Guttman-Kaiser rule or Scree plot is generally used. The Guttman-Kaiser (Unity) rule selects all principal components with a eigenvalues greater than 1.0. Since the total variance of all principal components is p, this Unity rule of 1.0 represents the variance of one variable if the variance were distributed equally among all the variables. The Scree plot is a plot of the eigenvalues, λ_i, versus i. The appropriate number of principal components is determined by looking for the bend in the curve. For many sets of data, the first several components will have high eigenvalues and the remaining will be small. In this analysis, both techniques were used. Based on these rules, the first d principal components were selected to define the information associated with the original data. Thus, the dimensionality of the data has been reduced from many variables to a few principal components.

4.1.2 Principal Axis Factoring (Factor Analysis)

Principal Axis Factoring (PAF) tries to identify the latent factor or underlying structure that "represent the common variance of variables, excluding unique variance, and is thus a correlation-focused approach seeking to reproduce the intercorrelation among the variables" (Garson, 2006). An iterative algorithm is used to calculate the factors based on **R.** The p common factors should include the non-diagonal correlations of **R** plus part of the diagonal element that is usually 1.0. In the case of PCA, the diagonal elements of **R** remain at 1.0. With PAF, the diagonal elements are less than 1.0 as explained below. The diagonal elements can be partitioned into:

$$\mathbf{R_{ii}} = h_i^2 + S_i = 1 \qquad 4.4$$

where h_i^2 is known as the communality, the variance that is common with all variables and S_i is the unique variance for all variables. With each iteration, **R** will include the same off-diagonal Pearson product-moment correlations but the diagonal elements will be the communalities h_i^2. S_i can initially be estimated by 1- the square of the multiple correlation coefficient of the ith X variable with all the other X variables.

Then, the initial $h_i^2 = 1 - S_i$

These h_i^2 become the diagonal elements of $\mathbf{R_k}$ (the iterative **R** matrix) and the eigenvalues and eigenvectors are determined until a convergence of the eigenstructure is obtained. The final common factors (eigenvectors) $\mathbf{e_i}$ are solved with:

$$(\mathbf{R_k} - \lambda_i \mathbf{I})\ \mathbf{e_i} = \mathbf{0}$$

and the factor scores are $\mathbf{z} = \mathbf{e}' (\mathbf{X} - \boldsymbol{\mu})$

The correlation between the common factors and the original variables are known as factor loadings. Factor loadings of 0.300 or more are usually considered significant to the factor structure (Child, 2006). The communality for a variable is also defined as the sum of squared factor loadings across all factors. From this perspective, a low communality for a variable indicates that it is not contributing to the latent factor structure. A communality of 0.2 or less was indicative that a variable was not highly correlated with the other variables in the factor analysis. In most cases, the variables would be deleted from the factor analysis (Child, 2006). If the factor loading was 0.300 for each of two factors, then the communality would be 2 x $(0.300)^2$ or 0.18, This agrees with the previously stated minimal value of 0.200 for a significant communality. Thus a factor loading of 0.300 and a commonality of 0.200 are consistent measurables; both indicate a low correlation among the variables and the variables would not be considered well-suited for factor analysis.

Three statistical tests are used to examine the correlation matrix for appropriateness of factor analysis. The Barlett's test for sphericity and the Kaiser-Meyer-Olkin test are usually used with a factor analysis. The Barlett's test for sphericity tests for significant correlations, a condition necessary for factor analysis. It tests whether the correlation matrix is an identity matrix (SPSS, 2006). Its probability of significance should be .000 for a factor analysis to be conducted. The Kaiser-Meyer-Olkin (KMO) test is a test for sampling adequacy relative to the number of variables and should be 0.5 or higher. The KMO test is the ratio of the sum of the squares of all the correlations of the variables in the factor analysis (all factors) compared to the same sum plus the sum of all bivariate partial correlations. Thus, the sum of the bivariate partial correlations must be relatively small for a high KMO test statistic. As a result, if one or two variables define the correlation structure, the KMO test statistic will be low. In addition, some education researchers prefer Cronbach's alpha as a measure of reliability for a factor. Cronbach's alpha is usually used for an (survey) instrument to indicate a measure of internal consistency (reliability) among questions about a particular subject. In factor analysis, it is use to determined if the variables used in one factor have internal consistency. The statistic is based on the average correlation and the number of variables for each factor. Whereas the KMO test statistic includes bivariate correlations across all variables in all factors in the factor analysis, the Cronbach's alpha includes the correlations associated with only one factor. Their combined use can complements each other. The Cronbach's alpha statistic is usually greater than 0.4. (Marques de Sá, 2003; Johnson and Wichern; 1998, Child, 2006; Kim and Mueller, 1978; Cronbach, 1951, SPSS, 2006)

To represent the factors in a rotated space, an orthogonal rotation routine of the factor axes is typically used. The most common technique is the Varimax rotation which includes an orthogonal rotation of the factors. In the case of two variables and two factors, the rotation can be viewed as the rotation of the axes so that the variance of the first factor is maximized and the two factors, Y_1 and Y_2 , are uncorrelated. The Anderson-Rubin method for factor scores was used to estimate the factor score coefficients such that the factor scores are scaled to an average of zero with zero correlation between factor scores (SPSS, 2006).

4.2 Factor Analysis Approach with the Empirical Data

4.2.1 Factor Analysis Process

Nine factor analyses were conducted using the 2004 student cohort; one for each pillar of student academic success. A research consideration was whether to run a factor analysis on the entire freshman cohort for a specific pillar or to run independent factor analyses for each student sector. A latent structure for the entire cohort was desired. Because the research plan included comparison of the factors across student sectors, it was necessary for the factor analysis to include all four-student sectors. Figure 4-1 illustrates the factor analysis process.

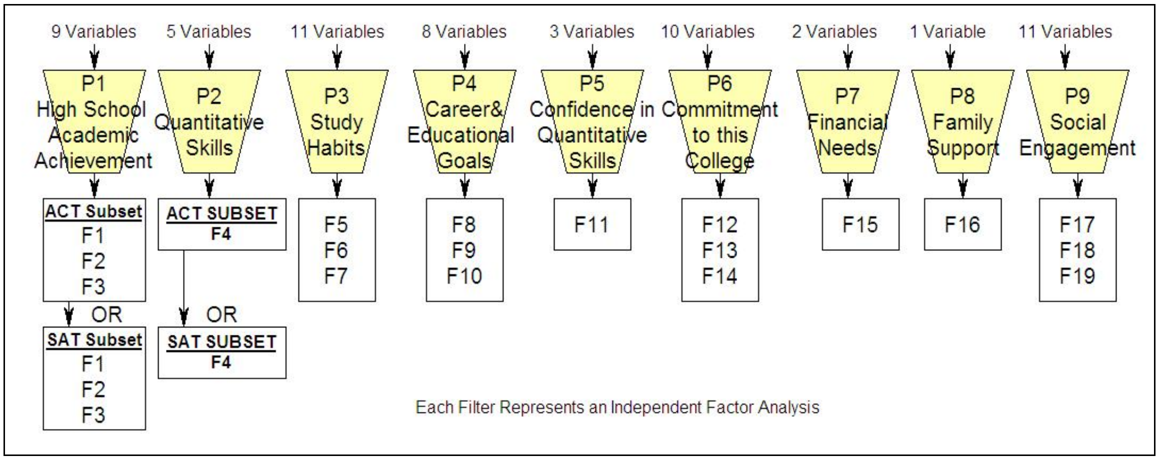

Figure 4-1 Process Flow of Factor Analysis

The pillars and factors are listed in Table 4-1 of this chapter.

SPSS 15.0 for Windows was used with the Principal Axis Factor method to extract the factors for the 2004 cohort and the Varimax method was used to rotate the factors. The Anderson-Rubin Method was used to calculate the factor scores for both the 2004 and 2005 cohorts. All variables included in the factor analyses were represented in the factor scores.

Because a student could report either the ACT or SAT test, the SAT and ACT subsets were considered separately. Note in Figure 4-1 that there are two P1 and P2 factor groups; one for the factors associated with ACT variables and another for factors associated with the SAT variables.

The following procedure was used for the factor analyses.

1. The correlation matrix was examined. The Bartlett's test of sphericity required a probability of significance of .000, to proceed with a factor analysis. Next, the KMO Measure of Sampling Adequacy was examined for a value of .5 or more.
2. The factor analysis was run on the 2004 cohort using the principal axis factoring method and the Varimax rotation. If the communalities table showed extraction communality less than .200, these variables were flagged as possible variables to delete from the factor analysis.

3. In determining the number of factors, the Unity rule (eigenvalue >1.0) was used and the Scree plot was reviewed. Then the factor analysis was rerun with one less and one more factor than that generated by the Unity rule. In some cases, the solution did not converge and a factor analysis was not completed.
4. The rotated factor loadings were examined for patterns of factors (high loadings for a variable related to a factor and low loadings for the other factors). The best pattern dictated the number of factors used. Labels were given to each factor based on the high factor loadings with the original variables
5. If the flagged variables (from 2. above) had low factor loading coefficients in the rotated matrix (less than .400), they were considered for deletion from the analysis. In some cases, dropping lowly-correlated variables will make other variables load better on fewer factors. The final decision of whether to delete a variable was based on an examination of the factor loadings with and without that variable.
6. There were a few outliers in the data. Because of the amount of data (over 1000 students' records) in the factor analysis, the outliers did not affect the factor analysis. The factor analyses were run with the outliers included.
7. The SPSS listwise option was used for missing data. If one variable's value was missing, that observation was not included in the analysis.
8. After the final factor structure was determined, the factor analysis was rerun using the Anderson-Rubin method to compute and store the factor scores for both the 2004 and 2005 cohorts. Labels were attached to the latent factors to identify the nature of the factor based on the highest factor loadings with the variables.

The sample sizes for the factor analyses ranged from 1232 to 1638.

4.2.2 Examination of Deleted Variables from Factor Analysis

A factor analysis was run on each pillar. In some cases, individual variables dropped out of the analysis as not highly correlated with the other variables in that pillar. An attempt was made to consider them for another pillar's factor analysis. The following procedure was followed:

1. Because the factor analysis is being conducted to enter the factors into a regression on the first year GPA, the correlation of each deleted variable with the first year GPA was computed. It would need a strong correlation with the first year GPA to strengthen the factor in the regression analysis.
2. If this correlation was statistically significant ($p<.05$) and the correlation was greater than .100, the variable was further considered.
3. The correlation of the variable with each of the factors was calculated. If one of the factors of a pillar had a significant correlation with the variable, it was considered for a new factor analysis (with that pillar). To further consider it, a subjective judgment was made as to whether the variable would make logical sense as a possible variable in the latent factor structure of the pillar under consideration.
4. All possible candidates for a different factor structure were then analyzed with a new factor analysis. To be further considered, the extracted communality needed to be at least .200. If this was the case, the usual rules for factor analysis were applied. As a final test, to be considered in a factor structure, the factor analysis with the new variable in it, needed to have a higher cumulative initial eigenvalues and a higher extracted sums of squared loadings. This would indicate that adding this variable was an improvement over the initial factor structure.

4.3 Factor Analysis Results

In this section, the summary statistics for the nine factor analyses (one for each pillar) are discussed. In addition, the examination of the deleted variables is discussed.

4.3.1 Overall Factor Analysis Statistics

From the factor analyses, nineteen factors were established. As an overall measure of a successful factor analysis, the KMO statistic and Barlett's test for sphericity was used. For all nine factor analyses, the KMO statistic was at least .500 and the probability of significance associated with Barlett's test of sphericity was .000. As a summary of the factor analyses, Figure 4-2 plots the cumulative percent of the eigenvalues (total variation) and the cumulative percent of the factor loadings for each pillar.

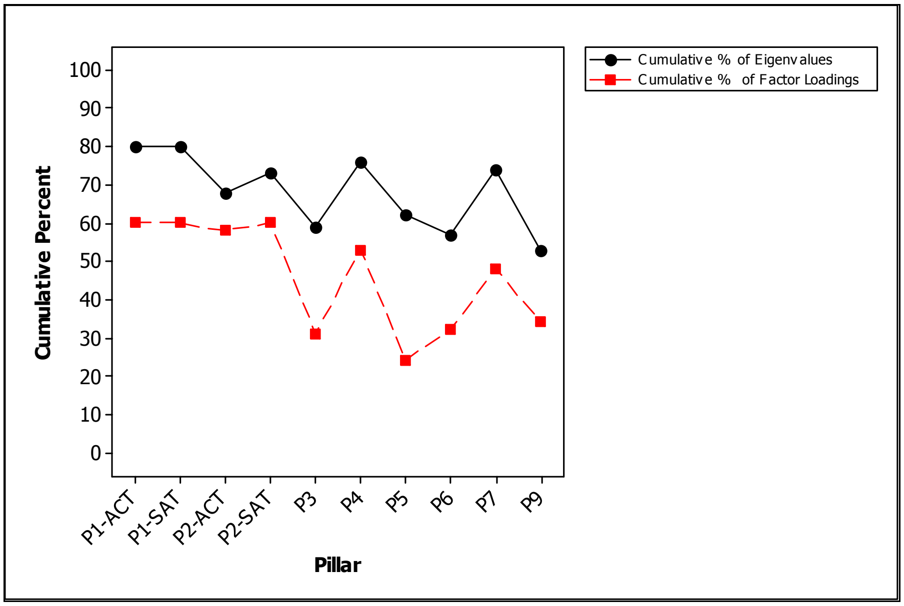

Figure 4-2: Cumulative Percent of Eigenvalues and Cumulative Factor Loadings for each Pillar

The cumulative percentage of the eigenvalues represents the percent of the total variation (both common and unique) associated with the selected factors for a pillar. The cumulative percent of factor loadings represents the percent of the common variation associated with the selected factors for a pillar. P8 (Family Support) is not included because P8 includes only one variable.

4.3.2 Communalities, Factor Loadings and Cronbach's Alpha for each Factor

Table 4-1 displays the communalities for each variable, factor loadings of the variables that are highly loaded on a factor, and Cronbach's alpha for each factor. The higher the communality for a variable, the better it "fits" in the latent factor structure. The factor loading is the correlation between the variable and each factor and only factor loadings with an absolute value of 0.3 or higher are listed in Table 4.3. Cronbach's alpha statistic is listed for each factor as a measure of internal consistency of scales (Cronbach, 1951). In practice, an alpha greater than .7 indicates high consistency, .4 to .7, moderate consistency and less than .4, poor consistency.

Table 4-1: Commonalities, Factor Loadings and Cronbach's Alpha

Pillar	Factor Score	Variable	Communality h_i^2	Factor Score Loading (Rotated)	Cronbach's alpha
P1 High School Academic Achievement (ACT Subset)	F1 High School Grades	High School GPA	.956	.969	.979
		High School Rank	.963	.960	
	F2 High School Performance	ACT Composite	.468	.662	.558
		Self-rating of academic ability	.433	.578	
		Self-rating of intellectual self-confidence	.379	.348	
	F3 High School Leadership	Self-rating of leadership ability	.383	.615	.448
		Self-rating of intellectual self-confidence	.379	.508	
P2 High School Academic Achievement (SAT Subset)	F1 High School Grades	High School GPA	.958	.974	.981
		High School Rank	.970	.970	
	F2 High School Performance	SATI Total	.414	.633	.559
		Self-rating of academic ability	.511	.602	
		Self-rating of intellectual self-confidence	.374	.325	
	F3 High School Leadership	Self-rating of leadership ability	.335	.572	.516
		Self-rating of intellectual self-confidence	.374	.518	
		Self-rating of academic ability	.511	.336	

Table 4-1: Commonalities, Factor Loadings and Cronbach's Alpha

Pillar	Factor Score	Variable	Communality h_i^2	Factor Score Loading (Rotated)	Cronbach's alpha
P2 Quantitative Skills (ACT Subset)	F4 Quantitative Skills	ACT Math	.754	.868	.842
		Math Placement	.638	.799	
		Chemistry Placement	.468	.684	
		ACT Science	.459	.677	
P2 Quantitative Skills (SAT Subset)	F4 Quantitative Skills	SATI Math	.687	.829	.815
		Math Placement	.681	.825	
		Chemistry Placement	.441	.664	
P3 Study Habits	F5 Study Habits Communicate With Professors	Frequency of asking a teacher for advice after class	.475	.642	.551
		Hours/week in past year spent talking with teachers outside class	.276	.525	
		Chance in the future to communicate with professors	.183	.422	
	F6 Study Habits Homework	Hours/week in past year on homework	.565	.703	.447
		Frequency of student felt overwhelmed	.272	.405	
		Frequency of studying with other students	.167	.323	
	F7 Study Habits Class Attendance	Frequency of: came late to class	.214	.461	.232
		Frequency of: student felt overwhelmed	.167	.319	

Table 4-1: Commonalities, Factor Loadings and Cronbach's Alpha

Pillar	Factor Score	Variable	Communality h_i^2	Factor Score Loading (Rotated)	Cronbach's alpha
P4 Commitment to Career and Educational Goals	F8 Choice of Major and Career	Chance will change major field	.719	.854	.843
		Chance will change career choice	.742	.841	
	F9 Educational Goals	Importance in decision to go to college : to prepare for Graduate/Prof School	.615	.695	.615
		Highest academic degree aspiration	.482	.687	
	F10 Career Goals	Importance in decision to go to college: Get training for specific career	.408	.567	.478
		Importance in decision to go to college: Be able to make money	.214	.463	
		Importance in decision to go to college: to prepare for Graduate/Prof School	.615	.363	
P5 Confidence in Quantitative Skills	F11 Confidence in Quantitative Skills	Self-rating of math Skills	.249	.499	.400
		Self-rating of computer skills	.249	.499	

Table 4-1: Commonalities, Factor Loadings and Cronbach's Alpha

Pillar	Factor Score	Variable	Communality h_i^2	Factor Score Loading (Rotated)	Cronbach's alpha
P6 Commitment to this College (U-M)	F12 Goals-UM Reputation	Importance in Choice of this college : Grads get good jobs Ranking in National Magazines Academic Reputation Social Reputation	 .432 .264 .270 .121	 .653 .506 .501 .322	.550
	F13 Goals-UM Choice	Choice of this institution Number of other applications to colleges	.526 .401	-.659 .631	.573
	F14 Goals-UM Financial Aid	Importance of choice of this college: My first choice did not offer financial Aid I was offered Financial Aid	 .354 .199	 .551 .443	.402
P7 Financial Needs	F15 Financial Needs	Amount of Loans for freshman year, Concern about financial aid	.479 .479	.692 .692	.649
P8 Family Support	F16 Family Support	Parents' Education level (maximum of either parent)	N/A	N/A	N/A

Table 4-1: Commonalities, Factor Loadings and Cronbach's Alpha

Pillar	Factor Score	Variable	Communality h_i^2	Factor Score Loading (Rotated)	Cronbach's alpha
P9 Social Engagement	F17 Social Engagement-Socializing	Hours/week in past year partying	.801	.895	.591
		Hours/week in past year socializing with friends	.275	.519	
		Chance will join a social fraternity or sorority	.211	.404	
		Self-rating of social self-confidence	.113	.307	
	F18 Social Engagement-Volunteer	Hours/week in past year in student clubs	.772	.877	.525
		Hours/week in past year in volunteer activities	.151	.350	
		Chance will participate in student clubs/groups	.251	.327	
	F19 Social Engagement-Activities	Chance of Studying Abroad	.326	.550	.460
		Hours/week playing video/computer games	.202	-.443	
		Chance will participate in student clubs/groups	.251	.379	

4.3.3 Variables Deleted from Factors Analysis

Of the sixty-one variables, thirteen were found not to fit into the latent factor structure of the nineteen factors. These thirteen variables are listed in Table 4-2.

An analysis, as described section 4.2.2, suggested that none of these variables were strong candidates for a latent factor structure for another pillar in the model. Any additional variables should add to the predictiveness of the regression on first year GPA; therefore, only variables that had a high correlation with the first year GPA were considered. Seven of the variables, listed in Table 4-2, had a significant correlation with the first year GPA. For these variables, correlations were computed with all the factors; then the factor analyses were rerun with the variables that were reasonable possibilities for a latent factor structure. The results are displayed in Table 4-3.

Of the seven variables, only "self-rating of drive to achieve" was a strong possibility for another factor structure. The communality for "self-rating of drive to achieve" in the High School Academic Achievement pillar was greater than 0.400 for both the ACT and SAT subsets.. Because this pillar includes either the ACT Composite score or the SATI Total score, there are two subsets and therefore two factor analyses (see Figure 4-1). For both factor analyses for this pillar, the extracted sums of squares of loadings with "self-rating of drive to achieve" included in the factor structure was compared to the extracted sums of squares of loadings with "drive to achieve" not included. The extracted sums of squares of loadings indicates the percent of variation of the common variance that is explained by the factors. With the addition of a significant variable, the extracted sums of squares of loadings should show an increase. Table 4.4 displays the sums of squares statistics, with and without the "drive to achieve" variables for both the ACT and SAT subset factor analyses. For both subsets of the High School Academic Achievement pillar, the extracted sums of squares of loading was less with "self-rating of drive to achieve" included than with the original set of variables. Therefore, it was concluded that 'self-rating of drive to achieve" did not add significantly to the factor analysis and no change was made in the original factor structure.

Table 4-2: Variables That Did Not Fit into a Factor Structure and Their Correlation with First Year GPA

Variables	Pillar	Correlation with First Year GPA
Self-rating of cooperativeness	P1 High School Academic Achievement	-0.014
Self-rating of writing ability	P1 High School Academic Achievement	0.126*
Hours per week in the past year spent reading for pleasure	P3 Study Habits	-0.010
Frequency of using the Internet for research or homework	P3 Study Habits	0.013
Frequency of tutoring another student	P3 Study Habits	0.054*
Importance in deciding to go to college: "to learn more about things that interest me	P3 Study Habits	0.062*
Self-rating of drive to achieve	P4 Commitment to Career and Educational Goals	0.085*
Importance of making a theoretical contribution to science	P4 Commitment to Career and Educational Goals	-0.092*
Self-rating of creativity	P5 Confidence in Quantitative Skills	-0.014
Importance of coming to this college: My relatives wanted me to come here	P6 Commitment to this College (U-M)	-0.011
Chance in the future you will be satisfied with this college	P6 Commitment to this College (U-M)	-0.004
Hours per week in past year working for pay	P9 Social Engagement	-0.055*
Chance in the future you will play varsity/intercollegiate athletics	P9 Social Engagement	-0.128*

* indicates statistical significance ($p<0.05$)
Note: The sample size for the correlations vary from 1612 to 1633

Table 4-3: Consideration of Deleted Variables in a Factor Analysis of a Second Pillar

Variables Considered As Factors (Correlation with first year GPA Is significant)	**Pillars Considered With a factor in pillar and r >0.100)**	**Maximum Correlation ** Of Variable With Factors Within Pillar**	**Extracted Communality (proportion common variance)**
Self-rating of writing ability	High School Academic Achievement (ACT subset)	0.224	0.147 in initial FA
	High School Academic Achievement (SAT subset)	0.267	0.200
	Study Habits	0.121	0.038
Frequency of tutoring another student	High School Academic Achievement (ACT subset)	0.157	0.125
	High School Academic Achievement (SAT subset)	0.118	0.037
	Study Habits	0.120	0.127 in initial FA
	Social Engagement	0.160	0.100
Importance in deciding to come to college to “learn more about thing that interest me”	Study Habits	0.119	0.042 in initial FA
	Commitment to Educational and Career Goals	0.161	0.070
	Social Engagement	0.184	0.079
Self-rating of drive to achieve	High School Academic Achievement (ACT subset)	0.435	0.401
	High School Academic Achievement (SAT subset)	0.440	0.420
	Study Habits	0.181	0.112
	Commitment to Educational and Career Goals	0.181	0.099 in initial FA*
	Commitment to this College	0.245	0.149
	Social Engagement	0.171	0.135

Table 4-3: Consideration of Deleted Variables in a Factor Analysis of a Second Pillar (Continued)

Importance of making a theoretical contribution to science	High School Academic Achievement (ACT subset)	0.110	0.153
	High School Academic Achievement (SAT subset)	0.126	0.042
	Quantitative Skills (ACT subset)	0.136	0.027
	Quantitative Skills (SAT subset)	0.218	0.064
	Commitment to Educational and Career Goals	0.197	0.081 in initial FA
	Confidence in Quantitative Skills	0.260	0.157
	Commitment to this College	0.108	0.102
Hours per week in past year working for pay	Study Habits	-0.138	0.048
	Financial Needs	0.126	0.025
	Social Engagement	0.152	0.038 in initial FA
Chance in the future you will play varsity/intercollegiate athletics	High School Academic Achievement (ACT subset)	-0.136	0.128
	High School Academic Achievement (SAT subset)	-0.122	0.067
	Social Engagement	0.141	0.037 in initial FA

* "in initial FA" indicates that the variable was originally entered into this pillar's factor analysis (FA)

** The maximum correlation is in terms of absolute value; the sign is indicated for the correlation with the highest magnitude. Note: the sample size for the correlations vary from 819 to 1608.

Table 4-4: Cumulative Extracted Sum of Squares Table With and Without the "Drive to Achieve" Variable

Factor	Initial Eigenvalues Cumulative Percent		Extracted Sum of Squares Cumulative Percent	
ACT Subset				
	Without "Drive to Achieve"	With "Drive to Achieve"	Without "Drive to Achieve"	With "Drive to Achieve"
F1 High School Grades	38.2	33.5	35.6	31.0
F2 High School Performance	62.2	50.4	50.9	41.9
F3 High School Leadership	80.0	74.1	59.7	57.5
SAT Subset				
F1 High School Grades	37.7	33.1	35.2	30.7
F2 High School Performance	61.7	51.1	51.1	41.7
F3 High School Leadership	80.0	74.3	59.4	57.3

4.4 Discussion

Based on the factor structure, commonalities, factor loadings, KMO statistic, Bartlett's test, and Cronbach's alpha, the overall latent structure showed favorable characteristics for a factor analysis. Some pillars showed a stronger factor structure than others; a discussion follows on the strength and weaknesses of the factor analyses.

Examination of the commonalities, factor loadings, Cronbach's alpha (Table 4-1) and the cumulative factor loadings (Figure 4-2) indicates that the following Pillars have a strong factor structure:

- P1 High School Academic Achievement
- P2 Quantitative and Analytical Skills
- P4 Commitment to Career and Educational Goals
- P7 Financial Needs

With a Cronbach's alpha greater than 0.7, F1 (High School Grades), F4 (Quantitative Skills), and F8 (Choice of Major and Career) indicate a high degree of consistency (often referred to as reliability). This is consistent with the high commonalities and factor loadings.

The following Pillars have a weaker factor structure:

- P3 Study Habits
- P5 Confidence in Quantitative Skills
- P6 Commitment to this College (U-M)
- P9 Social Engagement

Based on the nature of the questions asked in the CIRP survey, P3 (Study Habits) was expected to have a stronger factor structure. The weaker structure for Study Habits may suggest that for a highly selective university (or, specifically, at this university), other questions are more appropriate than the questions selected. All the bivariate correlations among the variables were .4 or less. With lower correlation coefficients, a weaker factor structure is expected as indicated by the commonalities, factor loadings and Cronbach's alphas.

F7 (Study Habits Class Attendance) had the lowest Cronbach's alpha of .232. This may be an artifact of the factor structure and not an issue of major concern. Only two variables were highly loaded on this factor: Frequency of came late to class (factor loading of .461) and Frequency of felt overwhelmed with everything I had to do (factor loading of .319). The Pearson correlation of these two variables was only .132. Frequency of felt overwhelmed with everything I had to do was cross-loaded on F6 (Study Habits) with a higher factor loading of .405. It is common in practice to consider any factor loading of .300 or more as significant and therefore include all variables with a factor loading > .300 in the Cronbach's alpha statistic. Since the .319 factor loading of "Frequency of felt overwhelmed with everything I had to do" is close to .300, an argument can be made that this may not be a significant factor loading, since it is already loaded on F6 (Study Habits Homework) at a higher loading. With this assumption, there is only one significant variable in F7 (Study Habits Class Attendance), i.e. Frequency of came late to class for the Cronbach's alpha. In this case, with one variable, the alpha cannot be calculated. More variables relevant to homework questions in high school and attendance of classes would be a recommendation for future research.

P5 Confidence in Quantitative Skills is based on only two questions; they were the most appropriate questions in the CIRP survey for addressing confidence in quantitative skills. More questions relative to confidence in quantitative skills would have been preferred for this pillar.

In the pillar, P6 (Commitment to this College (U-M)), F12 (Goals-U-M Reputation) and F14 (Goals-U-M Financial Aid) included only questions from the CIRP survey section on the importance of the reasons for choosing this college. These CIRP questions were designed with institutional commitment as the focus of the question. The order of the factor loadings for F12 (Goals –U-M Reputation) is very consistent for what would be expected for a highly selective academic-oriented research university with "Grads get good jobs" producing the highest factor loading of .653. The Cronbach's alpha of .402 was weaker for F14(Goals-UM Financial Aid) than for the other two factors in this pillar. This was probably due to only two questions being included in the calculation of this alpha and survey questions being related to financial aid. F13 (Goals U-M Choice) was based on a question on whether Michigan was the first choice college and how many other applications were sent to other schools (indicating indecision on Michigan as first choice or uncertainty about being accepted by Michigan). Its Cronbach's alpha of .573 was the highest for this pillar.

For P9 (Social Engagement), the factor loadings are logical and the overall structure is strong with a KMO test score of .621. In this case, preference is given to the KMO test score over the Cronbach's alphas (.591, .525 and .460), which are in the moderate range. The KMO test score > 0.5 indicates a strong sampling adequacy across the three factors.

The commonalities ranged from .113 to .970, representing the percent of total variance that is common for all the factors in a pillar. Child (2006) recommends commonalities of at least .200. Five variables had a communality less than .200. These included Frequency of studying with other students; Importance in choice of this college- social reputation, and - I was offered financial aid; Self-rating of social self-confidence; and Hours/week in past year in volunteer activities. All five variables were included because the rotated factor loading was .300 or higher. As part of the factor analysis, factor loadings were compared with these variables included and not included. The final decision was based on the number of factors, the number of variables and the rotated factor loading distributions. Preference was given to variables that loaded high primarily on one factor (and low on the others), and increased the percent of common variance across the factors.

The analysis of variables deleted from individual factor analyses indicated that they did not contribute significantly to the correlation structure of another factor analysis.

4.5 Summary

The sixty-one variables chosen from the CIRP survey and student performance data were factored into nineteen factors using the Principal Axis Factoring method. To understand the latent structure and minimize the effect of multi-collinearity on regression analyses, a factor analysis was run on each pillar of student success variables.

Overall, the factor analysis was considered successful. Of the factor structures that were developed, most were considered to have either a moderate or strong factor structure with the variables that were chosen. All the KMO test statistics were at least .500. The high school GPA and rank had the highest factor loadings and communalities > .900. Except for F7 (Study Habits Class Attendance), all factors had moderate to strong values for Cronbach's alpha, indicating internal consistency of response to the survey questions.

As indicated in the discussion, some of the factor structures were weaker than expected (but still considered to have moderate strength as a factor structure). When more variables were considered, the percent of common variation was about the same and the factor structure was more difficult to interpret; i.e. more variables did not contribute to a stronger factor structure.

For reference purposes, the overall model is shown in Figure 4-3 and the factors are listed in Table 4-1 and in Appendix B.

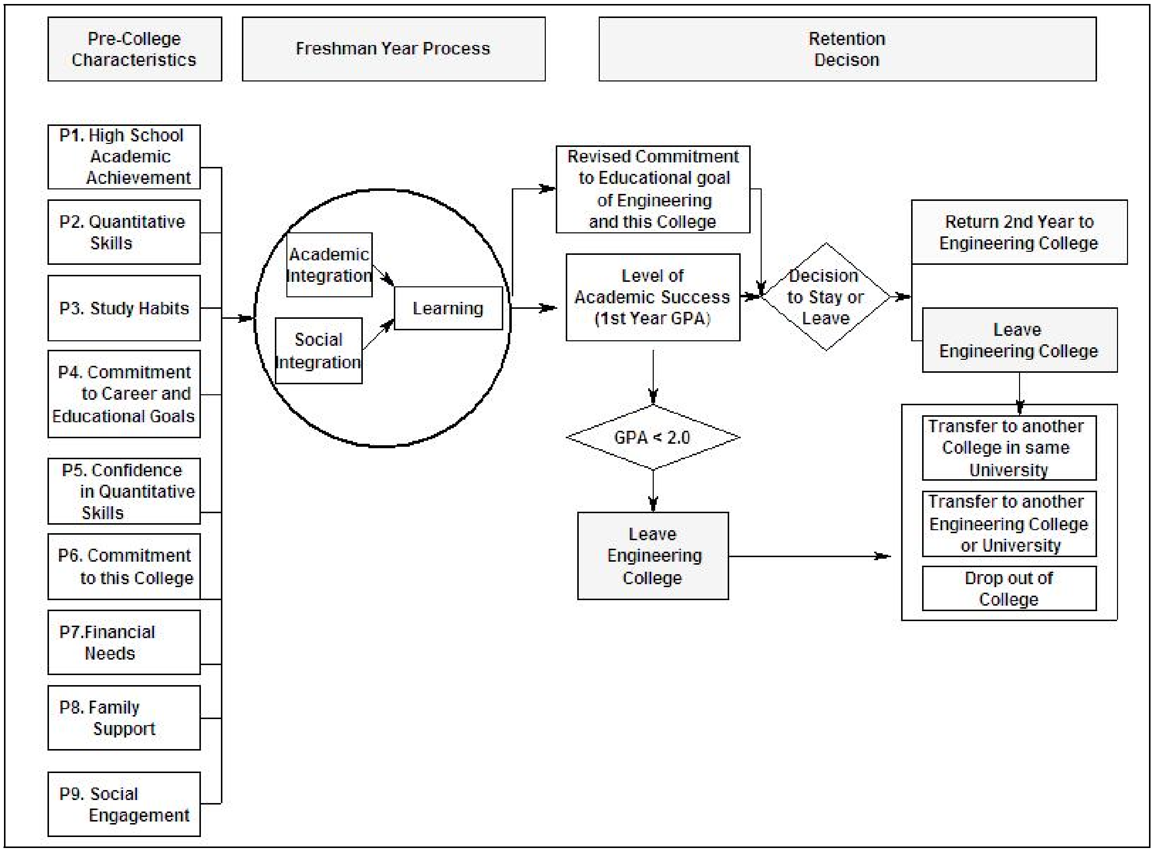

Figure 4-3: Student Success Model

CHAPTER V
MODELING OF ACADEMIC SUCCESS
FOR THE ENGINEERING STUDENT SECTOR

Chapter V and Chapter VI together model student success in the engineering student sector. This chapter discusses the modeling of engineering student *academic success (first year GPA)*. Chapter VI discusses the modeling of engineering student *retention (probability of returning to engineering after the freshman year)*. Figure 5.1 displays the topics covered in these two chapters.

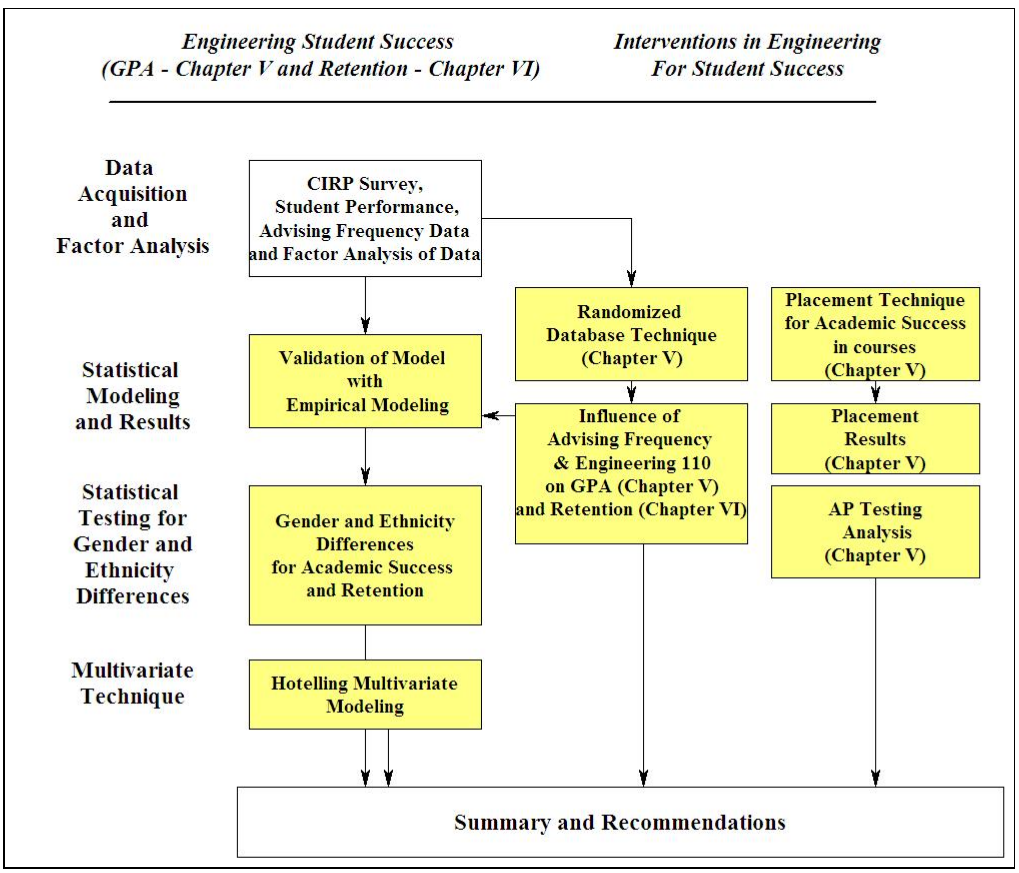

Figure 5-1: Content of Chapters V and VI

In Section 5.1, the contribution of each pillar of student success to first year GPA is discussed. In Section 5.2, a prediction equation of first year GPA based on the pre-college characteristics is presented. The prediction equation of the ACT subset is compared to the prediction equation of the SAT subset's prediction equations. In addition, the predictability for a second cohort is discussed for both the ACT and SAT subsets. In addition, in this section, the Hotelling's T^2 is discussed for its modeling potential. This technique identifies outliers in a multivariate control chart approach and describes the stability of the underlying multivariate structure. Section 5.3 discusses the statistical hypothesis testing of differences in gender and ethnicity relative to the model.

Sections 5.4 and 5.5 discuss the influence of interventions on academic success for engineering students. Consider this question: What techniques can be used to improve the development of best practices for academic success? If we can identify the students who need help, and then provide them with the support that will help them succeed, then we can transform these actions into policies and practices for engineering academic success. Currently, we do not know which programs for academic integration (i.e. intervention programs) are the MOST effective for academic success. At the same time, public universities like Michigan have limited funds for student support. In Section 5.4, a set of guidelines for interventions based on the proposed model are presented. In addition, three intervention programs for academic success are discussed. The first is a mentoring program (Section 5.4.1). As part of my doctoral research, I studied the success of a mentoring program for academic success in the College of Engineering. This program was successful in improving academic integration of struggling students and is described in this chapter. In Section 5.4.2, the two other interventions, advising frequency and enrollment in Engineering 110, are discussed.. The advising support was provided by the Engineering Advising Center. Although the Engineering 110 course is not a traditional "intervention" program, it was studied as a possible intervention program for motivating students towards an engineering career. Engineering 110 is currently an elective course on the survey of engineering courses. Although I found more support in the literature that motivation towards an engineering career improved retention, I also studied the effect of enrollment in Engineering 110 on academic success and it is discussed in this Section 5.4..

A technical issue related to the analysis of intervention programs is the "happenstance" nature of the data (i.e., data collected without experimental control). Students decide to participate in one or more programs. A researcher surveys participants of an intervention program and analyzes some data from the program. It is generally unknown which other intervention programs in which students have participated. If a group of students participated in several programs together, the results could be biased just because of this fact. In Section 5.4.3, a randomized database technique based on statistical randomization concepts was developed and explored to address this issue. In analyzing this intervention data, the significant predictors from the model were used to control the pre-college characteristics. If there are significant differences between students who participated in an intervention and students who did not, the effect of the pre-college characteristics has been taken into account.

Also covered in this chapter as an independent research topic related to academic success, is first course placement (Section 5.5). In the late 1990's, Purdue University researchers showed that the first term GPA was a predictor of graduation and that correct placement was important (Budny, et al., 1998). Veenstra and Herrin (2006a) used the ACT Math score to predict academic success in the freshman engineering courses. F4 (Quantitative Skills) was considered as an improvement over the ACT Math as a predictor of academic readiness for each of the freshman level engineering courses. My research suggests that the concern is not just placement into pre-calculus or Calculus I, but also into the higher-level math courses. In Section 5.5, modeling of placement into freshman level courses based on F4 (Quantitative Skills) is considered. A discussion of academic performance in Calculus II based on the AP test scores is also provided.

The empirical research on academic success was limited to first-time, full-time students, whose freshman engineering class matriculated in the fall of 2004 and 2005.. The factors from the factor analyses described in Chapter IV were used as predictors of academic success. The word “factor” is used both in factor analysis and to indicate a variable in an analysis of variance table. To avoid confusion, the factors from the factor analysis will be referred to by factor ***number*** such as F1 or F4 and factors in an analysis of variance will be referred by name, such as Gender.

In summary, Section 5.1 covers the validation of the model developed in Chapter II; Section 5.2 develops the prediction equation for academic success (first year GPA); and Section 5.3 discusses differences in the average first year GPA by gender and ethnicity within the context of the model. Section 5.4 discusses intervention programs for student success and the randomized database technique while Section 5.5 discusses using the Quantitative Skills factor as a placement instrument for student success in the freshman level courses and the placement of AP Calculus students. Section 5.6 summarizes the chapter.

5.1 Validation of the Academic Success Model by Pillar

5.1.1 Methodology

Figure 5-2 displays a copy of Figure 4.1 of the factors associated with each pillar. In order to validate that these pillars were significant contributors to the model, each set of factors associated with a pillar were entered into a regression linear model. The first year GPA was the dependent variable.

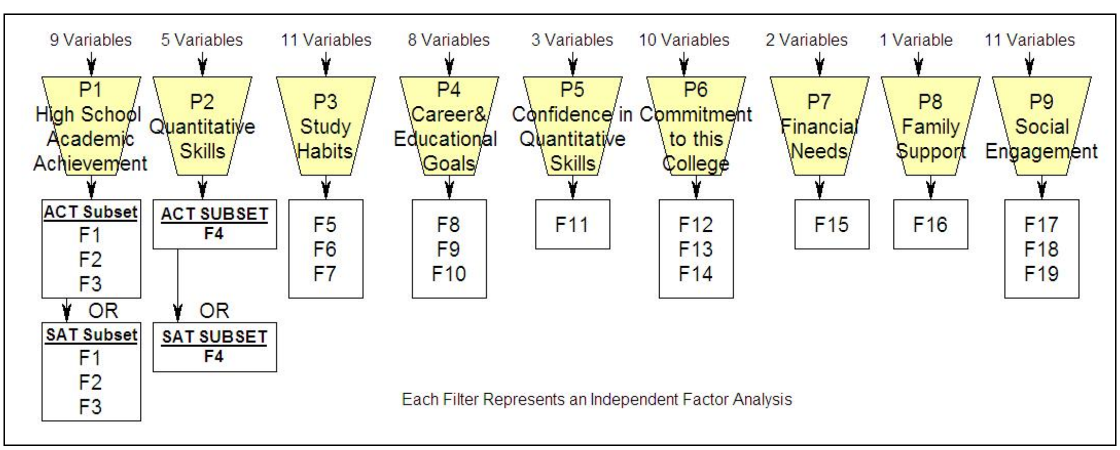

Figure 5-2: Factors Associated With Each Pillar of Academic Success

For example, for pillar P1, the model for the jth student can be represented as:

$$GPA_j = \beta_0 + \beta_1 F_1 + \beta_2 F_2 + \beta_3 F_3 + \varepsilon_j$$

Within a pillar, the factors are uncorrelated with each other. The adjusted R^2 represents the true proportion of variation in first year GPA that is explained by the factors in this pillar. The adjusted R^2 statistics were used to rank the pillars by their contribution of explained variance of the first year GPA. The adjusted R^2 and the p-value of the F-test associated with the regression were used as measures of predictability. With the F-test for the regression, it was possible to statistically determine if the pillar was significant in the development of the model.

5.1.2 Validation Results

To validate the significance of a pillar, multiple regressions were run for EACH pillar. For each of the nine regressions (one for each pillar), all the factors were forced into the regression. As an example, P1 consists of three factors. All three factors were entered into the regression. As a result, it was possible to estimate the relative importance of each pillar in its contribution to the model, in terms of explained variation of first year GPA. The adjusted R^2 was used as the statistic to measure the explained variation for each regression. The F-statistic for the regression was used to indicate whether there was overall statistical evidence of significance of a pillar in the model.

The results in Table 5-1 clearly show that most of the pillars have a significant F- statistic in predicting the first year GPA, with P1 and P2 explaining the most variability in first year GPA. The sample size was 184 for the ACT subset and 161 for the SAT subset. Because some students report only the ACT or SAT test scores, there is a difference in the sample sizes of these two subsets.

TABLE 5-1: Validation of the Contribution of each Pillar to First Year GPA for the Engineering Sector (Pillars ordered by their Adjusted R^2)

Model's Pillar For Student Success*	ACT Subset (n=184)		SAT Subset (n=161)	
	Adj. R^2	Regression F p-value	Adj. R^2	Regression F p-value
P1. High School Academic Achievement	.262	.000	.295	.000
P2. Quantitative Skills	.231	.000	.179	.000
P8. Family Support	.039	.004	.056	.001
P5. Confidence in Quantitative Skills	.041	.003	.032	.014
P4. Commitment to Career And Educational Goals	.048	.008	.025	.074
P7. Financial Needs	.019	.035	.002	.252
P9. Social Engagement	.008	.225	.029	.053
P6. Commitment to this College	.000	.489	.023	.086
P3 Study Habits	.000	.562	.011	.189

*** A separate regression was run for each pillar. The independent variables were all the factors for that pillar and the dependent variable was first year GPA.**

5.1.3 Discussion

High School Academic Achievement and Quantitative Skills Are Major Contributors to Academic Success with at least 18% Explained Variation

The regression results on first year GPA confirmed the strong effect of P1 (High School Academic Achievement) and P2 (Quantitative Skills). P1 (High School Academic Achievement) explained 26% of the total variation in the first year GPA for the ACT subset and 30% for the SAT subset. P2 (Quantitative Skills) explained 23% of the total variation in the first year GPA for the ACT subset and 18% for the SAT subset.

Family Support and Confidence in Quantitative Skills Each Explain 5%

In addition, for both subsets, P8 (Family Support) and P5 (Confidence in Quantitative Skills) showed significant effects for first year GPA, with each pillar explaining about

5% of the total variation. Between the ACT and the SAT subsets, the effects of P4 (Commitment to Career and Educational Goals), and P7 (Financial Needs) were mixed. These factors were significant in one of the subsets, not both (using a significance level of .05).

Some Pillars were not Significant Contributors to Academic Success

Neither pillars P3 (Study Habits), P6 (Commitment to this College (Michigan)) nor P9 (Social Engagement) showed a significant effect for either subset. This finding was somewhat surprising. For the ACT subset, none of the regression coefficients were statistically significant (See Tables C-3, C-6 and C-9 in Appendix C). The maximum magnitude of the correlation coefficients of these factors with the first year GPA was only 0.15. For the SAT subset, for each of these three pillars, one regression coefficient was significant but the overall regression was not significant. Within the P3 (Study Habits) pillar, F7(Study Habits-Class Attendance) was significant (p=.031, Table C-12 in Appendix C), but the overall (regression) F-test was not significant (p=.189). Within the P6 (Commitment to this College) pillar, F12 (Goals- UM Reputation) was statistically significant (p=.039, Table C-15 in Appendix C), but the overall (regression) F-test was not significant (p=.086). Within the P9 (Social Engagement) pillar, F17 (Social Engagement- Socializing) was significant (p=.007, Table C-18 in Appendix C) but the overall (regression) F-test was not significant (p=.053).

5.2 Significant Factor Predictors for First Year GPA

This section discusses the modeling of freshman engineering academic success (first year GPA) from the factor scores.

5.2.1 Methodology

The validation results of Section 5.1 showed the strength of EACH pillar in a general predictive sense for first year GPA. It indicates the percent of total variation in the first year GPA that can be attributed to each pillar. It does not provide a predictive equation for academic success (i.e. first year GPA) from the pillars. To predict the first year GPA, the individual factors must be used as predictors across all the pillars. In this section a prediction equation for academic success (first year GPA), will be developed using the 19 factors from the nine pillars. A model for first year GPA is shown in equation 5.1. Desirable in this model is a set of factors that explain the most variation with the least number of factors and a low level of multi-collinearity.

$$GPA_j = \beta_0 + \beta_1 F_{xj} + \beta_2 F_{yj} + \ldots + \beta_3 F_{zj} + \varepsilon_j \qquad 5.1$$

To achieve this, both best-subset regression and stepwise regression were used together. The adjusted R^2, Mallows Cp and residual standard deviation were considered in the final regression. The adjusted R^2 is the percent of variation in the GPA explained by the factors in the model, adjusted for the number of predictors. Mallows Cp gives a measure of the amount of bias in the regression equations. A guideline for Mallows' Cp is that it be close to the number of predictors. For each factor that is added, a decrease in the residual standard deviation should be obtained. 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. In the modeling, interactions among the significant factors were tested for significance. GPAs of less than 1.0 were considered outliers and not included in the regressions.

Once the significant factors were defined, a Hotelling's T^2 control chart was used to

1) determine the students whose factors were not consistent with the multivariate space of the identified factors.

2) explore the stability of the process.

Those data points that were considered "in control" from the Hotelling's T^2 were then entered into the stepwise regression again to determine a final linear model. The Hotelling' T^2 is defined in matrix notation as:

$$N\,(\mathbf{X} - \boldsymbol{\mu})'\,\mathbf{S}^{-1}\,(\mathbf{X} - \boldsymbol{\mu})$$

where N is the sample size, **X** is the matrix of factor scores, **μ** is the vector of averages of the factor scores, and **S** is the variance-covariance matrix of the factors. The Upper Control Limit is based on the F distribution.

The Minitab for Windows 15.0 and SPSS 15.0 were used to generate the regressions, plots and Hotelling T^2.

5.2.2 Regression Results (Including Hotelling's T^2)

As previously described, the research design included two subsets; a subset including records of students who reported the ACT scores and a subset of students who reported the SAT scores. There was research interest in comparing the predictability of the first year GPA between these two subsets. In addition, there was research interest in whether a prediction would be valid for more than one freshman year cohort. Therefore, the predictions using the ACT and SAT subsets were based on the 2004 cohort. These prediction equations were then applied to the 2005 cohort as a cross-validation for a second year. If the adjusted R^2 was as high for the 2005 cohort as for the 2004 cohort, it would indicate that the prediction equation could be used for more than one year. The results for the ACT and SAT subsets and cross-validation discussion are provided in this section.

ACT Subset Regression Results

For the 2004 cohort, the regression modeling of first year GPA results using the ACT subset is shown in Table 5-2.

Most of the predictiveness occurred with the first two predictors, F4 (Quantitative Skills) and the F1 (High School Grades) x F4 (Quantitative Skills) interaction, yielding an adjusted R^2 of .33. As more predictors entered the regression, the Cp decreased, leading to less bias of the regression coefficients. (Cp should be approximately equal to the number of predictors for no bias in the coefficients.)

Table 5-2: Stepwise Regression Results for Modeling of Academic Success for the ACT Subset for the 2004 Cohort (N=184)

Predictor	Coefficient	T	P	Adj. R^2	Mallows Cp
Constant	2.921	63.70	.000		
F4 (Quantitative Skills)	0.233	6.17	.000	0.231	46.2
F1 x F4 Interaction	0.205	4.58	.000	0.331	17.9
F1 (High School Grades)	0.113	2.92	.004	0.349	13.6
F11(Confidence in Quantitative Skills)	0.096	2.41	.017	0.365	9.8
F10 (Career Goals)	-0.087	- 2.37	.019	0.381	6.2

F10 (Career Goals) entered in this regression with a negative coefficient. This was difficult to understand. Including it reduced the effect of the F4 (Quantitative Skills) and decreased the bias in the regression coefficients (based on the Cp statistic). For the ACT subset, the correlation between F10 (Career Goals) and first year GPA is -.132 and was statistically significant (p=.022). F10 (Career Goals) also has a significant negative correlation of -.162 with F4 (Quantitative Skills).

SAT Subset Regression Results

For the 2004 cohort, the regression modeling of first year GPA results using the SAT subset is shown in Table 5-3.

Most of the predictiveness occurred with the first three predictors, F4 (Quantitative Skills), F1 (High School Grades), and F2(High School Performance), yielding an adjusted R^2 of .32, indicating that 32% of the variation was explained by these factor scores . Both F7 (Study Habits class Attendance) and F10 (Career Goals) entered into the regression model with negative coefficients and accounted for another 4% of the explained variation. The interaction of F1(High School Grades) x F4(Quantitative Skills) entered the regression as a significant predictor but explained only another 1% of the variation. With the interaction included, the regression coefficients were relatively unbiased, as indicated by a Mallows' Cp of 6.6.

Table 5-3: Stepwise Regression Results for Modeling of Academic Success for the SAT Subset for the 2004 Cohort (N=161)

Predictor	Coefficient	T	P	Adj. R^2	Mallows Cp
Constant	3.024	73.15	0.000		
F4 (Quantitative Skills)	0.131	2.49	0.014	0.179	51.0
F1 (High School Grades)	0.198	4.56	0.000	0.279	26.5
F2(High School Performance)	0.141	2.89	0.004	0.318	17.4
F7 (Study Habits Class Attendance)	-0.109	-2.98	0.003	0.344	12.0
F10 (Career Goals)	-0.084	-2.24	0.026	0.360	9.0
F1 x F4 (High School Grades x Quantitative Skills Interaction)	0.093	2.11	0.037	0.374	6.6

Comparison of the Regressions from the ACT and SAT Subsets and Cross-Validation

Table 5-4 shows the summary of the regression results for the ACT and SAT subsets. Using the 2004 cohort as the basis for the regression coefficients in the model of first year GPA, both the ACT and SAT subsets yielded approximately the same percent of explained variation (adjusted R^2) and the same Cp value. Cp measures the amount of bias in the regression coefficients. A value of 6 for Cp represents an unbiased estimate for 5 to 6 predictors and indicates a reasonable prediction equation.

In Table 5-4, the major difference between the ACT and SAT subset statistics is in the adjusted R^2 for the cross-validation with the 2005 cohort. The R^2 has been used as an indicator of good cross-validation of cohorts and "model generalizability" in the literature (French, et al., 2005). The cross validation will be discussed next.

Table 5-4: Summary of Regression Results for First Year GPA for Engineering Using the 2004 cohort and Cross-Validation with the 2005 Cohort

Subset	Number of Significant Factors	Adjusted R^2 (2004 Cohort)	Mallows Cp (2004 Cohort)	Validated Adjusted R^2 On 2005 Database
ACT subset	5	0.38 (n=184)	6.2	0.36 (n=177)
SAT Subset	6	0.37 (n=161)	6.6	0.17 (n=150)

ACT Subset Cross-Validation with the 2005 cohort

The ACT subset for the 2005 cohort shows good cross-validation with an adjusted R^2 of 0.36 compared to 0.38 for the 2004 cohort.. The conclusion is that the model can be generalized across cohorts.

SAT Subset Cross-Validation with the 2005 cohort

From Table 5-4, it can be seen that the proportion of total variation explained by the regression, (i.e., the adjusted R^2 of .17) was reduced by a factor of 2 in the cross-validated 2005 cohort SAT subset, compared to the 2004 cohort SAT subset, with which the regression was based. To understand this finding better, Table 5-5 summarizes three regressions using the 2005 cohort. The first regression (A.) was the cross-validation using the same predictors and the same estimates of the regression coefficients as used in the 2004 cohort. This is the standard cross-validation. The second regression (B.) forced the same predictors into the 2005 cohort regression with the regression program estimating the BEST LEAST SQUARES ESTIMATES of the coefficients. This regression examined the use of the same predictors as in the original regression but allowed the coefficients to be re-estimated using the 2005 cohort data. The effect was that a much higher R^2 (of 0.34) was generated (See Table 5-6).

The third regression (C.) was a stepwise regression with all nineteen factors and the F1 (High School Grades) x F4 (Quantitative Skills) interaction considered. In C., the regression was independent of the 2004 cohort regression and chose the best set of predictors from the nineteen factors (See Table 5-7) using stepwise regression.

Table 5-5: Comparison of Regressions on the 2005 Cohort for Academic Success

Regression	**S.E. Residual (√ MSE)**	**Adjusted R^2**
A. Cross-Validation: Same Predictors **AND** Same Regression Coefficients as 2004 Cohort	0.4498	0.17
B. Same Predictors Forced Into Regression and **Best Estimates** of Regression Coefficients are Determined by the Regression algorithm	0.4085	0.34
C. Step-wise Regression with All Factors (Selected Predictors are: F4(Quantitative Skills), F1 (High School Grades) x F4(Quantitative Skills), F7(Financial Needs), F1(High School Grades)	0.4057	0.34

The fit was much better with the latter two regressions. If the same predictors were used but the coefficients of the regression prediction were re-estimated, the adjusted R^2 was .34 compared to .37 for the original prediction with the 2004 cohort (Regression B, Table 5-6). Two findings were significant from Table 5-6:

1) Using the p-level for the t-test, three predictors that were significant for the 2004 cohort were not significant for the 2005 cohort. These predictors included: F2 (High School Performance), F7 (Study Habits Class Attendance) and F10 (Career Goals). This was also verified by the confidence interval on the coefficient including zero.

2) The coefficient for F4 (Quantitative Skills) from the 2004 cohort was significantly less than for the 2005 cohort since the coefficient was outside the confidence interval for the estimate of the coefficient from the 2005 cohort. The same was true for F7 (Study Habits Class Attendance) and F10 (Career Goals) but not relevant, since these factors were not significant with the 2005 data.

In the examination of the stepwise regression of the 2005 cohort (Regression C., Table 5-7), the most significant predictors for the 2005 cohort using the SAT subset were F4 (Quantitative Skills), the Interaction of F1 (High School Grades) x F4 (Quantitative Skills) and F15 (Financial Needs). The stepwise regression yielded a R^2 of 0.34, which was comparable to the 0.37 achieved with the 2004 SAT Subset, but with a different set of variables as predictors.

In summary, the poor cross-validation with an R^2 of only 0.17 was explained by the finding that different predictors are significant for the 2005 cohort than for the 2004 cohort.

Table 5-6: Forced Regression for the 2005 Cohort with the Same Predictors that Were Significant from the 2004 Cohort for the SAT Subset

Predictor	Coefficient From 2004 Cohort Regression	2005 Cohort Regression Forced with Same Predictors as Was Significant in the 2004 Cohort (N=150)				
		Coefficient (Forced)	t-test	P-level t-test	95% Confidence Interval for Coefficient	
					Lower	Upper
Constant	3.024	3.005	57.71	0.000	2.902	3.108
F4 Quantitative Skills	0.131*	0.273	3.89	0.000	0.134	0.412
F1 High School Grades	0.198	0.104	2.04	0.044	0.003	0.204
F2 High School Performance	0.141	0.074	1.38 (N.S.)	0.170	-0.032	0.179
F7 Study Habits Class Attendance	-0.109*	0.021	0.62 (N.S.)	0.538	-0.047	0.089
F10 Career Goals	-0.084	0.045	1.25 (N.S.)	0.214	-0.027	0.117
F1 x F4 Quantitative Skills x High School Grades Interaction	0.093	0.146	2.83	0.005	0.044	0.248

* Coefficient outside confidence interval for coefficient of 2005 Cohort

Table 5-7: Comparison of Stepwise Regressions of the 2005 Cohort to the 2004 Cohort for the SAT Subsets

Predictor	Coefficient From 2004 Cohort Regression	2005 Cohort Stepwise Regression (N=150)		
		Coefficient	**t-test**	**p-level**
Constant	3.024	2.992	59.54	0.000
F4 Quantitative Skills	0.131	0.331	6.56	0.000
F1 High School Grades	0.198	0.095	1.91	0.058
F2 High School Performance	0.141	Not Included		
F7 Study Habits Class Attendance	-0.109	Not Included		
F10 Career Goals	-0.084	Not Included		
F1 x F4 Quantitative Skills x High School Grades Interaction	0.093	0.133	2.59	0.011
F15 (Financial Needs)	Not Included	-0.066	-1.99	0.049

Note: F1 (High School Grades) has a $p>0.050$. It was included because of the hierarchy rule concerning interactions, i.e., if an interaction (F1 x F4) is included in a regression model, the main effects must be too.

Decision to Use the ACT Subset for a Regression Model

Because of the SAT subset yielded a much smaller cross-validation R^2 for the 2005 cohort, the decision was made to model first year GPA with the ACT variables and ACT subset. All subsequent modeling of the first year GPA is based on the ACT subset.

The prediction equation for academic success (first year GPA) is:

$$\begin{aligned}GPA = 2.921 &+ \\ &0.233\ F4\ \text{(Quantitative Skills)} + \\ &0.113\ F1\ \text{(High School Grades)} + \\ &0.205\ F1xF4\ \text{(High School Grades x Quantitative Skills)} + \\ &0.096\ F11\ \text{(Confidence in Quantitative Skills)} - \\ &0.087\ F10\ \text{(Career Goals)}\end{aligned} \qquad 5.2$$

F4 (Quantitative and Analytical Skills) was the first of five factors to enter the regression and explained 23% of the total variation in the GPA (See Table 5-3). The five predictors explain 38% of the variation. The coefficient for F10 (Career Goals) was negative. As previously discussed, this was difficult to explain.

One of the diagnostic graphs used to evaluate the residuals for patterns in regression modeling was a plot of the residuals versus the predicted value. Figure 5-3 illustrates the randomness of the residuals from the regression with the model of equation 5.2.

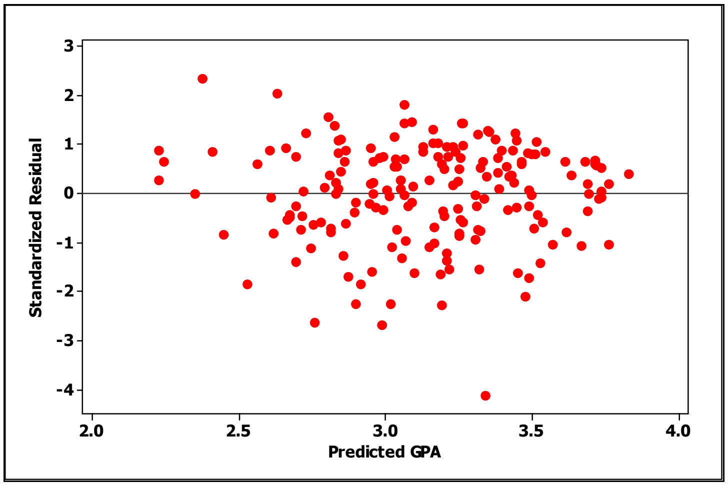

Figure 5-3: Plot of Standardized Residuals versus Predicted GPA (ACT Subset, n=184)

Examining Stability with Hotelling's T^2

To explore the stability of the multivariate X responses in the model, the factors identified in the regression equation 5.2 were entered into a Hotelling T^2 multivariate control chart analysis using Minitab. After three iterations of deleting outliers (a common practice), a stable control chart was obtained. (See Figure 5-4)

Examination of Figure 5-4 showed stability for T^2 and included 95% of the original sample. Most of the ten outliers represented students whose pre-college characteristics indicate a significantly less or higher level of a characteristic when compared to the "in control" data. The residual plot from Figure 5-3 with the outliers identified by open circles is shown in Figure 5-5. Based on the residuals, no significant patterns are present. Since some of the identified "outliers" have a positive standardized residual, this is an indication that the support programs in place or activities that occurred during the freshman year enabled students to achieve academically at a higher level than was predicted.

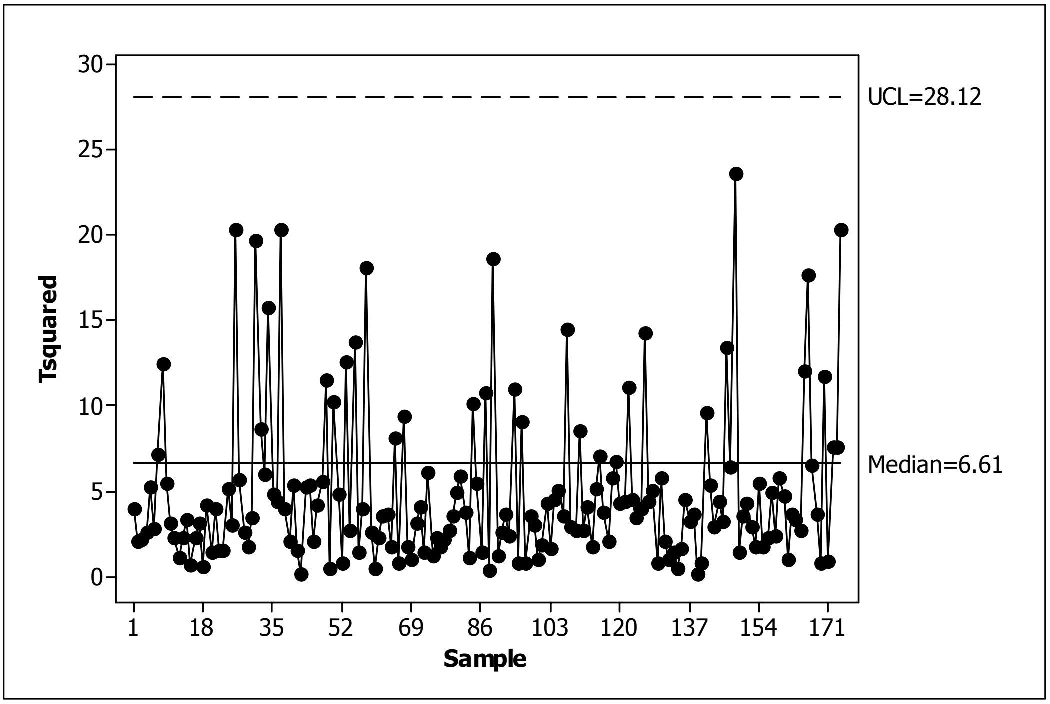

Figure 5-4: Hotelling's T^2 Multivariate Chart Shows Consistency of Data

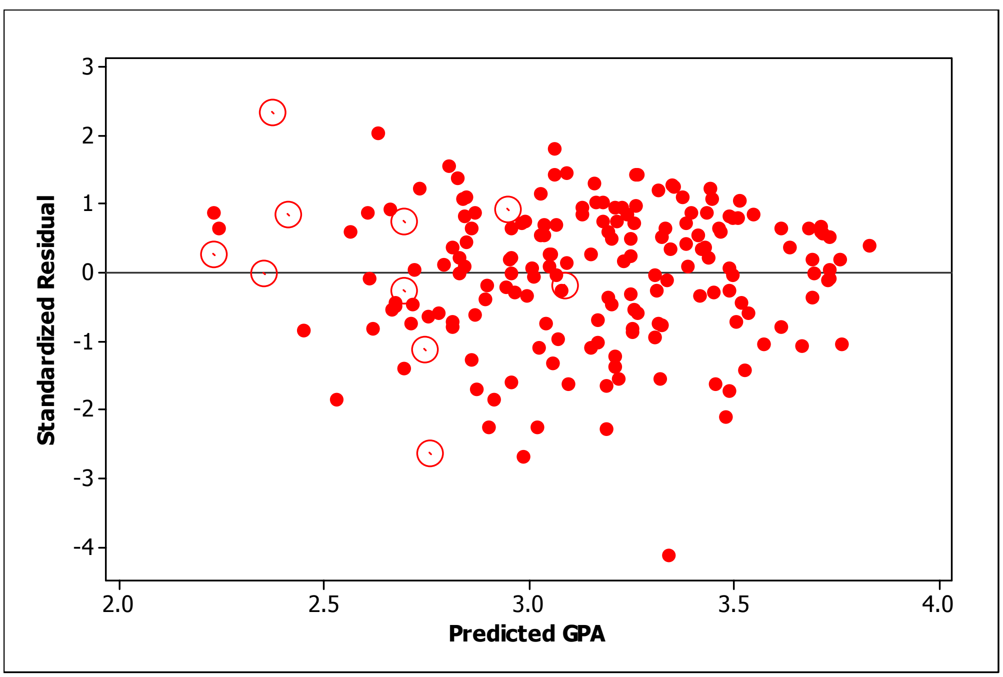

Figure 5-5: Plot of Standardized Residuals versus Predicted GPA with T^2 Outliers Identified by Open Circles (n=184)

5.2.3 Discussion

The Final Model for the First Year GPA

Using the ACT variables and subset, the modeling for first year GPA for the engineering sector was considered successful. The model for engineering academic success (first year GPA) is given as follows:

GPA = 2.921 + 0.233 F4 (Quantitative Skills) +
0.113 F1 (High School Grades) +
0.205 F1xF4 (High School Grades x Quantitative Skills) +
0.096 F11 (Confidence in Quantitative Skills)-
0.087 F10 (Career Goals) 5.2

To calculate the factor scores, the coefficients generated by the Anderson-Rubin method were used. The Anderson-Rubin method was discussed in Chapter IV. Anderson-Rubin generates a coefficient for each variable included in a factor analysis. Using these coefficients, the factor scores for predicting the first year GPA from Table 5-2 are calculated as follows:

F1 (High School Grades) = 0.603 High School Rank Percent
+0.442 High School GPA
-0.114 ACT Composite
-0.075 Self-Rating of Academic Ability
+0.035 Self-rating of Leadership Ability
-0.035 Self-rating of intellectual self-confidence

F4 (Quantitative Skills) = 0.501 ACT Math Score
+0.314 U-M Math Placement test score
+0.183 Chemistry Placement test score
+0.178 ACT Science Reasoning Score

F1 x F4 Interaction is calculated as the product of F1 and F4 as described above.

F11 (Confidence in Quantitative Skills)

= 0.632 Self-rating of math ability
+ 0.632 Self-rating of computer skills

F10 (Career Goals) = 0.616 Importance to go to college to get training for A specific career
+0.433 Importance to go to college to be able to make More money
+0.362 Importance to go to college to prepare for graduate/ Professional school
-0.381 highest degree recoded (see chapter III)
+0.080 Change Major Field
+0.046 Change Career Choice

With an adjusted R^2 of .38, **almost 40% of the variation in first year academic success (GPA) can be explained by five factors, consisting of pre-college student information**. The most significant of these factors, F4 (Quantitative Skills) accounted for 23% of the total variation in first year GPA. The next most significant predictor was F1 (High School Grades), which was highly loaded from the variables, high school GPA and high school rank. These two factors together explained 29% of the total variation in the first year GPA. The interaction between F1 and F4 was significant and explained another 6% of the variation for a total of 35%. The last two significant predictors were F11 (Confidence in Quantitative Skills) and F10 (Career Goals) were significant but contribute only another 3% to the adjusted R^2.

Hotelling's T^2

Hotelling's T^2 control chart showed exceptionally good stability among the student data in the ACT subset. Of 184 data points, only 5% of the data were identified as inconsistent with the mass of the data. In general, this 5% were considered as outliers with a lower levels of preparation, as indicated by F1 (High School Grades) and F4 (Quantitative Skills). Exploration of the data using Hotelling's T^2 suggested that this multivariate technique could be used to identify students who are in need of early academic intervention. With a Hotelling's T^2 analysis, students in need of intervention would be identified (as outliers) and examination of individual student records would show a value outside the normal range of statistical variation. . This would be useful to advising counselors.

5.3 Gender and Ethnicity Effects on Model for First Year GPA

This section examines whether there is a significant difference in the first year GPA based on gender or ethnicity, controlling for significant predictors of academic success from the modeling already conducted in Section 5.2. The 2004 cohort was used for this analysis.

In this analysis, ethnicity is summarized into two student categories: URM, which includes the under-represented minority students (Black, Hispanic and Native American races) and Non-URM, which includes the White and Asian races. International students are not included in the URM and Non-URM classifications of ethnicity.

5.3.1 Methodology

Two linear models were considered. The first includes only gender and ethnicity with a dependent variable of academic success. In the second model, the regression model of section 5.2 for academic success was extended to a linear model that includes gender and ethnicity. The significant factors from the regression model (equation 5.2) are included as covariates. The SPSS for Windows 15.0 generalized linear model program was used.

5.3.2 Results

Table 5-8 displays the average and standard deviation for the first year GPA and the significant model covariates by gender and ethnicity for the 2004 cohort.

Table 5-8 Averages and Standard Deviations of Regression Factors and GPA by Gender and Ethnicity Show Significant Differences

Variable/ Factor	Gender			
	Female (N= 48)		Male (N=135)	
	Average	**Std. Dev.**	**Average**	**Std. Dev.**
First Year GPA	3.064	0.542	3.166	0.548
F1 High School Grades	0.041	1.029	0.055	0.846
F4 Quantitative Skills*	0.148	0.890	0.760	0.846
F10 Career Goals	0.192	1.012	0.183	0.847
F11 Confidence in Quantitative Skills*	0.325	0.712	0.881	0.831
*Significant difference in the averages at p =.050 using an one-way analysis of variance				
Variable/ Factor	**Ethnicity**			
	URM (N=20)		**Non-URM (N=155)**	
	Average	**Std. Dev.**	**Average**	**Std. Dev.**
First Year GPA*	2.793	0.481	3.174	0.546
F1 High School Grades*	-0.556	1.597	0.112	0.746
F4 Quantitative Skills*	-0.149	0.820	0.665	0.876
F10 Career Goals*	0.629	0.653	0.140	0.892
F11 Confidence in Quantitative Skills	0.635	0.613	0.758	0.892
*Significant difference in the averages at p =.050 using an one-way analysis of variance				

When only gender and ethnicity status were included in a linear model (no covariates) with the first year GPA as the dependent variable, the adjusted R^2 was only .04. There was a significant effect by ethnicity (p=.006) but not by gender..

Once the covariates (F4 (Quantitative Skills), F1 (High School Grades), Interaction of F1 x F4, F11 (Confidence in Quantitative Skills), and F10 (Career Goals) were added to the model along with gender and ethnicity, the adjusted R^2 was .39. After controlling for the significant covariates, no significant difference in gender (p=.807) or ethnicity (p=.460) existed. (See Table 5-9). The F-statistic for a test in difference in gender controlling for the covariates is only .060 (p=.807); similarly, the F-statistic for difference in ethnicity (URM) is only .548 (p=.460).

TABLE 5-9 Linear Models on First Year GPA with Gender, Ethnicity And Covariates for Engineering

Dependent Variable: First Year GPA

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	22.164[a]	8	2.770	14.895	.000
Intercept	356.900	1	356.900	1918.810	.000
F4 Quantitative Skills	6.909	1	6.909	37.146	.000
F1 High School Grades	1.382	1	1.382	7.432	.007
F11 Confidence in Quantitative Skills	1.433	1	1.433	7.706	.006
F10 Career Goals	.863	1	.863	4.642	.033
F1xF4	4.001	1	4.001	21.509	.000
Gender	.011	1	.011	.060	.807
Ethnicity	.102	1	.102	.548	.460
Gender * Ethnicity	.360	1	.360	1.934	.166
Error	30.690	165	.186		
Total	1759.603	174			
Corrected Total	52.854	173			

a. R Squared = .419 (Adjusted R Squared = .391)

Note that the total degrees of freedom are 174 (instead of 184 for the ACT subset) due to missing data related to the ethnicity classifications.

5.3.3 Discussion

The following are the findings for academic success when gender and ethnicity are considered with a model that controls for the effect of the covariates.

- 39% of the total variation in First Year GPA is explained by the model
- After adjusting the averages of First Year GPA for the covariates, no statistically significant differences exist in gender or ethnicity.

In the initial analysis of the first year GPA, no difference existed in the average GPA between male and female students. This is consistent with the literature. For example, Hartman and Hartman (2006) provided average GPAs that showed that female engineering students earned GPAs slightly higher than male engineering students did.

The average difference of the first year GPA by ethnicity (URM and Non-URM students) can be explained by the covariates. To explore this finding in more detail, Figure 5-6 displays the average first year GPA and adjusted first year GPA (adjusted for the covariates) by ethnicity. Figure 5-6 clearly illustrates a large difference in the unadjusted average first year GPA between the URM and Non-URM student groups (solid line). It also illustrates that this difference is narrowed significantly, when the averages are adjusted for the covariates[5] (dashed line). Table 5-9 shows that this difference in the adjusted averages between URM and Non-URM students groups is not significant ($p=.460$). Since the covariates are primarily related to the P1 (High School Academic Achievement), P2 (Quantitative Skills), and P5 (Confidence in Quantitative Skills), the difference in ethnicity can be explained by different levels of preparation and confidence in quantitative skills. P4(Commitment to Career and Educational Goals) contributes to this difference with F10(Career Goals). F10(Career Goals) is the last factor to enter the stepwise regression and its contribution is weaker than the other factors. Interestingly, the URM students have a significantly higher F10(Career Goals) average than Non-URM students.

Support in the literature is present for this trend. Allen (1999) found that "pre-college academic ability (i.e. high school rank) was found to play a significant role on their [both minorities and nonminorities] cumulative grade point average."

In summary, there is no difference in the average first year GPA with respect to either gender or ethnicity, once the averages are adjusted (controlled) by the covariates with the model equation of 5.2.

[5] The average first year GPA is adjusted to the average for each covariate: F4=.576, F1=.034, F1xF4= .061, F10= .195, F11= .745

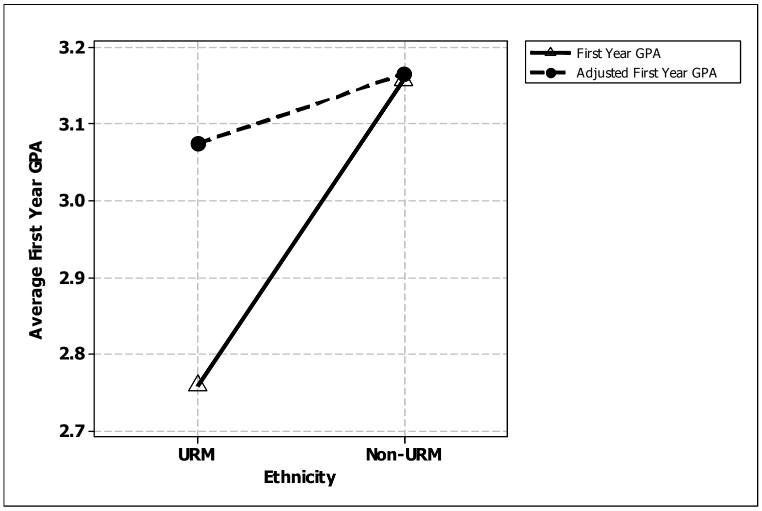

Figure 5-6 Comparison of Actual Average GPA and Adjusted Average GPA by Ethnicity

5.4 Interventions for Academic success

Researchers have shown that a strong relationship exists between the first term GPA in engineering and the engineering retention rate. (Budny, et.al., 1998, Scalise et.al., 2000) Student intervention programs that help student succeed academically are part of the student support function at engineering colleges. These programs include mentoring, tutoring, and advising. Course placement can also be considered as an intervention program since correct placement increases the student's probability of academic success (Budny, et. al., 1998).

As an example of how intervention strategies can connect to the model, Table 5-10 summarizes possible intervention strategies for student deficiencies in a pillar. In the Seymour and Hewitt study (1997), students indicated that when they realized they were in academic trouble, they could not get help soon enough. This implies a systematic and proactive approach by the university is needed to help students in academic trouble.

Table 5-10: Proposed Intervention Change Based on Pillars

Pre-college Characteristic Pillar	Measured By	Low Level Expected Effect on Student Success	Process Change	Effect
P1. High School Academic Achievement	H.S. GPA, H.S. Rank SAT Total ACT Composite	Less prepared academically, freshman courses challenging	Proper placement is key; directed tutoring, Advising support	Significant improvement in knowledge; leading to a good college GPA
P2. Quantitative Skills Math Skills	ACT Math SAT Math	Less prepared, may not be ready for calculus, residual effect on rest of engineering courses; at very high risk	1st term is key; proper placement into all courses, less course load; directed tutoring advising support	Enable student to be successful, early intervention a must.
P2. Quantitative Skills- Scientific Reasoning	ACT Science	Less prepared for chemistry and physics	Proper placement in science 1st term, directed tutoring, advising support	Enable student to be successful
P3. Study Habits	High School. hours/week studying	May not be able to Keep up with course load	Mentoring	Enable student to be successful
P4. Commitment to Career/Degree of Engineering	Indicator such as highest degree Sought CIRP variables	May drop out	Career mentoring or course on engineering careers; advising discussion of engineering careers by faculty in classes, establish peer community	Student persists

Table 5-10: Proposed Intervention Change Based on Pillars (continued)

Pre-college Characteristic Pillar	Measured By	Low Level Expected Effect on Student Success	Process Change	Effect
P5. Confidence in Quantitative Skills	Confidence Indicator, self-ratings	Even with good grades, student may drop out	Mentoring, career advising or course on engineering careers	Student persists
P6. Commitment to college the student is attending	Indicator whether this college was first choice	May drop out	Establish peer community in engineering	Student persists
P7. Financial Needs	Survey indicator	May drop out; financial needs not met	Financial advising	Student persists
P8. Family Support	Parents' level of education	May drop out	Parents' encouragement of student online parents' network	Student persists
P9. Social Engagement	Survey indicator of social engagement in high school	May drop out; may be over-challenged in courses that stress team work	Extra guidance on participating in dorm activities, small engineering club activities	Student persists

Currently, a university like Michigan will provide a number of intervention programs: mentoring, tutoring and advising. It is the responsibility of the student to take advantage of these programs. Table 5-10 provides a set of guidelines and suggests the paradigm that interventions can be applied in a systematic way to help all students, based on the pillars of student success.

Michigan supports its students with a number of intervention and support programs. The rest of this section will discuss three intervention programs available in the College of Engineering, for which data was available. These include:

1) Mentoring of first year students (Section 5.4.1)
2) Advising (Section 5.4.2 through 5.4.5))

3) Enrollment in Engineering 110 (Section 5.4.2 through 5.4.5)

Initially data on Engineering 110 was collected because it was an engineering course. From the data analysis, it became evident that Engineering 110 could be considered as an intervention, related to commitment to an engineering career.

5.4.1 Mentoring of First Year Students

This section summarizes a research effort that I led on the analysis of a first year mentoring effort for the 2004-2005 freshman class. Staff and volunteers under the leadership of the Associate Dean of Undergraduate Education in the College of Engineering conducted the mentoring. A more detailed report is available. (Chung, Koch and Veenstra, 2005)

The Academic Mentoring Program (AMP) is for students who are academically struggling. Generally, students are invited into the AMP mentoring program if they are on scholastic probation. For freshmen, this would include students who have been placed on academic probation with a first term GPA less than 2.0 (out of 4.0); they would be invited into the mentoring program for the second term of their freshman year. For this analysis, only AMP mentored students who carried a full credit load of 12 credits or more in the fall term were included in the analysis.

The analysis included a comparison of two groups of students: the 14 students who were mentored and a control group of 74 students. All students in either the mentored or control (non-mentored) group were full time in the fall term and earned a fall term GPA less than 2.0.

At the end of the winter term, both groups showed improvement in the winter term GPA over the fall term GPA.

- The Control group earned an average GPA for the winter term .56 higher than the fall term.
- The AMP mentoring group earned an average GPA 1.08 (one grade) higher than the fall term.

- Using a t-test for testing the difference in average GPA, the average improvement in the GPA of the AMP group over the control group was statistically significant with a p-value of .01.
- There was an average improvement of .52 for the AMP group compared to the Control group.

The conclusion from this research project was that implementation of mentoring in the winter term of the freshman year significantly contributed to academic success of academically struggling students.

5.4.2 Advising and Engineering 110

The Engineering Advising Center (EAC) advises freshmen on course selection and placement, career decisions and general counseling. Its role is to "provide academic advising services and support for first-year and undeclared students in their transition form high school to the rigorous academic demands of the College of Engineering" (University of Michigan, 2003). The EAC especially counsels students with low academic achievement. Advising data (related only to advising frequency) was collected and made available to this research. An advising frequency of four or less to the Engineering Advising Center was considered low and a frequency of more than four visits was considered high. (It is routine for a student to visit the EAC twice both semester for course counseling.) As a measure of engagement between each student and EAC, the number of visits per year for each student was collected and included in the research database. The following hypothesis was developed:

> Hypothesis 1: Students with a high level of advising visits will have a lower GPA than students with a low (routine) level of advising. This hypothesis suggests that there will be a correlation between the number of EAC visits and the first year GPA but that it is not a causal relationship.

Engineering 110 is a two-credit survey course in engineering careers. Approximately one-third of the students in the 2004 and 2005 cohorts enrolled in Engineering 110. The model development in Chapter II provides evidence that motivation towards an engineering career increases retention, but not the first year GPA. The following hypothesis was developed:

> Hypothesis 2: Enrollment in Engineering 110 will not have a significant effect of the first year GPA

5.4.3 Methodology- Randomized Database Analysis

The analysis of intervention programs is challenging for most researchers. The data tends to be "happenstance" data, i.e. data that is collected with no experimental control. It is generally recognized that students participate in several intervention programs. When a simple control-experimental samples approach is taken, bias may be generated due to students participating in more than one program. This section discusses an approach that was taken in the analysis of the data to minimize the inherent bias. Also significant with this analysis was that the testing of the hypotheses was conducted, controlling for the significant predictors in the model. (The predictors from equation 5.2 were covariates in a generalized linear model).

The approach to evaluating the effect of advising frequency and enrollment in Engineering 110 was to extend the generalized linear model used in Section 5.3 to include two new factors, a two-level advising frequency factor (low/high) and a two-level Engineering 110 factor (Yes, No enrollment) was desired. With the competing intervention programs, there could be a confounding effect between enrollment in Engineering 110 and another intervention such as a learning community effort. In traditional design of experiments, randomization is usually used to minimize this effect. Subjects would be randomly selected for a particular treatment, such as enrollment in a class. For example, the University of Maryland chose to control pre-college characteristics for evaluating the effectiveness of the first-year seminar by randomly assigning students to either be enrolled or not be enrolled in the seminar. (Goodman et al. 2006).

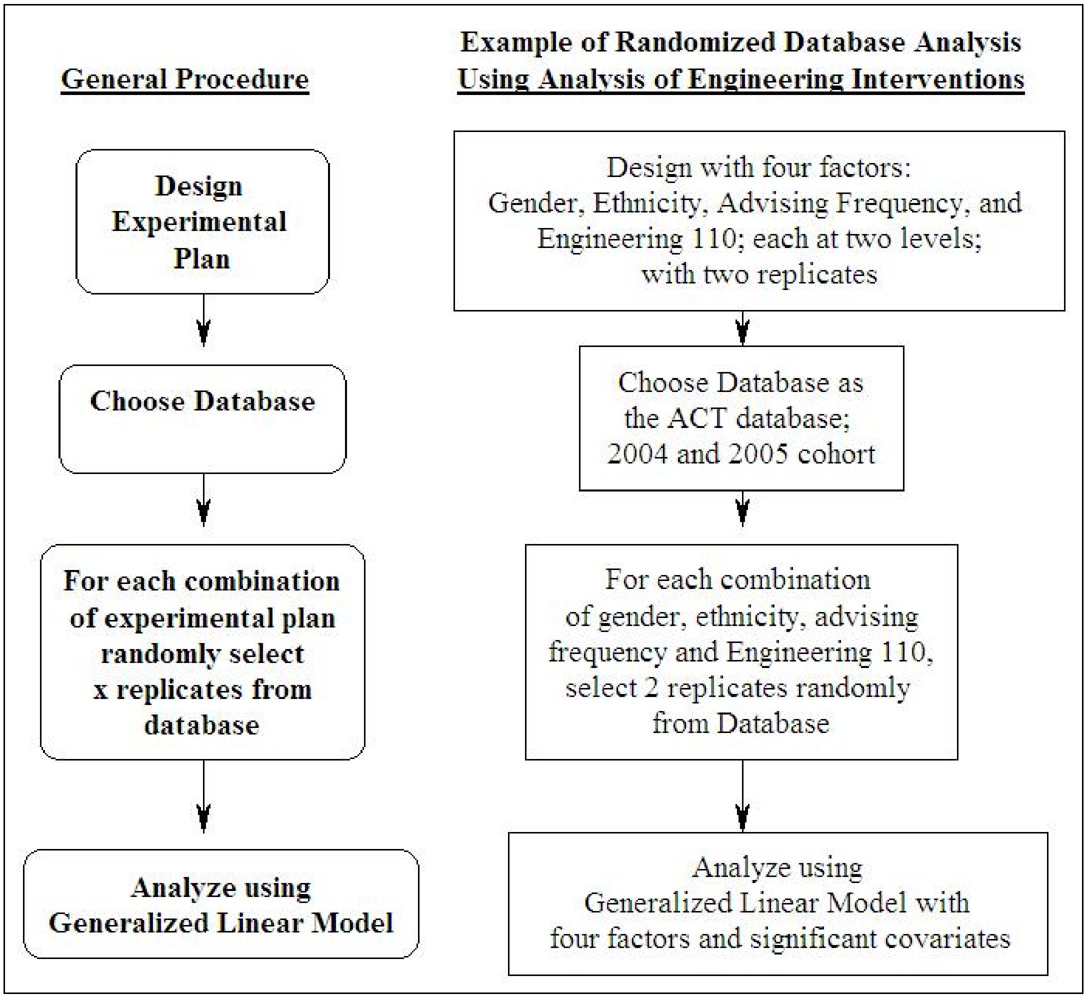

Figure 5-7: Flowchart of Randomized Database Procedure

In this research, students have already decided on the level of advising and course enrollment (i.e. they cannot be assigned to experimental groups). In order to minimize the confounding effect of interventions, students for the analysis were randomly selected from the database to ensure randomization and minimize the effect of other intervention strategies. Instead of randomly selecting the students from a large population with a particular characteristic (low or high advising frequency), students were randomly selected from the database. (See Figure 5-7)

A four-factor, 2-level 2^4 model was used with two replicates. This equates to 32 data; because of some missing data (levels not available as data in the database), the analysis include 27 data. The four factors were: Gender, Ethnicity (URM, Non-URM), Advising frequency (low, high), and Engineering 110 (enrolled, not enrolled). Because of missing data in one of the combinations, the four-way interaction could not be estimated. Insignificant interactions were pooled into the error term to achieve a valid analysis. A random number table was used for randomly selecting the observations from the database based on a dummy ID. (Beyer, 1991) In addition, the factor scores that were significant in the regression model were included as covariates. This approach will be referred to as a randomized database analysis.

5.4.4 Results Using the Randomized Database Analysis

The final Analysis of Variance Table for the generalized linear model associated with the randomized database analysis is shown in Table 5-11. An analysis showed that interaction effects with Ethnicity (URM) were not significant. In addition, the three way interactions were not significant and were pooled into the error term. Neither F10 (Career Goals) nor F11 (Confidence in Quantitative Skills) were significant; as a result their sums of squares were also pooled into the error term. The Interaction F1 x F4 (High School Grades x Quantitative Skills) is significant. By the hierarchy rule on pooling of sums of squares into the error sums of squares, F1(High School Grades) and F4 (Quantitative Skills) must also be in the model.

No main effects among the factors were significant. The p-values for the ethnicity, gender, advising frequency and Engineering 110 effects were all > .05. The significant interactions are Gender x Engin 110 (p=.020) and Advising x Engin 110 (p=.022). The plots of the average first year GPA for each of these interactions are shown in Figures 5-8 and 5-9

Table 5-11: Final Generalized Linear Model of First Year GPA Shows Significant Interaction between Enrollment in Engineering 110 and Advising Frequency

Dependent Variable: First Year GPA

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	6.428(a)	10	.643	3.714	.010
Intercept	142.447	1	142.447	823.096	.000
Ethnicity	.277	1	.277	1.600	.224
Gender	.019	1	.019	.112	.742
Advising	.576	1	.576	3.330	.087
Engin110	.005	1	.005	.027	.871
Gender * advising	.564	1	.564	3.257	.090
Gender * Engin110	1.161	1	1.161	6.710	.020
Advising * Engin110	1.114	1	1.114	6.437	.022
F4 Quantitative Skills	.195	1	.195	1.127	.304
F1 HS Grades	.008	1	.008	.045	.834
F1 x F4	1.372	1	1.372	7.927	.012
Error	2.769	16	.173		
Total	233.308	27			
Corrected Total	9.197	26			

a R Squared = .699 (Adjusted R Squared = .511)

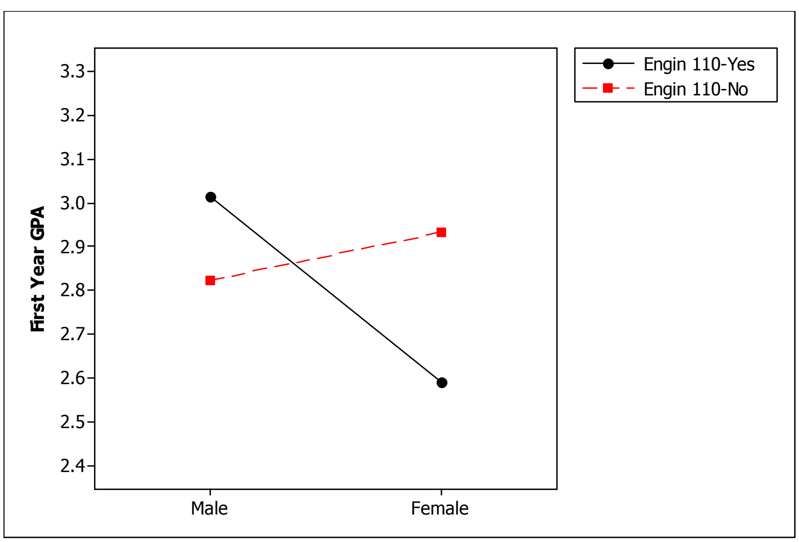

Figure 5-8 Plot of Average First Year GPA for the Interaction of Engineering 110 x Gender (n=27)

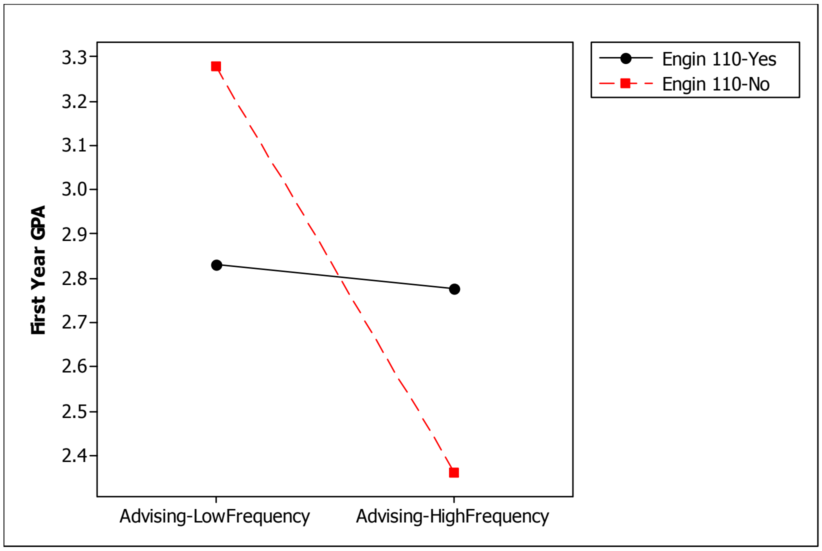

Figure 5-9: Plot of Average First Year GPA for the Interaction of Engineering 110 x Advising Frequency Suggests That the Combination of Engineering 110 and a High Advising Frequency Help Some Students (n=27)

5.4.5 Discussion of Interventions

Hypothesis 1 was stated as:

> The students with a high level of advising visits will have a lower GPA than students with a low level of advising.

This was not confirmed with the analysis. The difference in the average GPA between the low level and high level frequency of advising was not significant (p=.087).

Hypothesis 2 was stated as:

> Enrollment in Engineering 110 will not have a significant effect on first year GPA.

Consistent with Hypothesis 2, there was not sufficient evidence to indicate a significant effect due to the enrollment in Engineering 110 (p=. 871).

From Table 5-11, there were two significant interactions: Gender x Enrollment in Engineering 110 and Advising Frequency x Engineering 110. The interaction effect of Gender x Enrollment in Engineering 110 suggests that the course motivates male and female students differently for student success. (Figure 5-8). There was no main effect on a gender difference on first year GPA (p=.742). Yet, female students who enrolled in Engineering 110 earned a lower first year GPA; this GPA was substantially less than the GPA for female students, who did not enroll in Engineering 110. A review of the data showed that the female students who enrolled in Engineering 110 earned a lower average GPA for the entire 2004 engineering cohort. For the ACT subset. from which the data was sampled from, the average first year GPA was 2.94 (n= 17). This compared to an average of 2.60 for the sample of 6 female students included in the randomized database sample. Although the sample was lower, it was within random variation. The t-test for comparing the averages was 1.49 with a significance level of 0.171. A review of the F4(Quantitative Skills) statistics showed that the female students who enrolled in Engineering 110 had a substantially lower average. This is indicative of this group of students being less prepared in their quantitative skills. From the model, it would be predicted that the first year GPA would then be less. This pattern of averages for the first year GPA may have been specific to 2004 since in 2005 the average first year GPA of females who enrolled in Engineering 110 was higher than that of females who did not enroll in Engineering 110.

The students who visit the Engineering Advising Center at a higher frequency usually have more need for advising support for academic success. Therefore, it is not surprising nor a negative reflection on the Advising Center that the average first year GPA is less for students who have a high rate of advising frequency, compared to the average first year GPA of students with a low rate of advising frequency. What is significant is that students who both have a high rate of advising and enroll in Engineering 110 achieve a higher first year GPA (See Figure 5-9).

5.5 F4 (Quantitative Skills) as a Placement Indicator into Freshman Courses

Several researchers have shown the importance of correct placement into the first math and science courses in college. (Budny, 1998, Shuman, et. al., 2003, Koch and Herrin,

2006) Sadler and Tai (2007) found that years of high school mathematics was a significant predictor of academic performance in all college science courses.

In a paper published in 2006, Veenstra and Herrin provided evidence that the ACT Math score was a significant predictor of success in the freshman courses at Michigan. A contingency table approach was used to evaluate a ACT Math score of a 27 as a cutpoint predictor of earning at least a passing grade (C) in the first semester freshman courses. The efficiency of this instrument was at least 86% for all first semester STEM courses taken. The efficiency is “the percent of students whose grades were accurately predicted (less than or greater than/equal to a C) by the ACT Math score using a cut-point of 27” (Veenstra and Herrin, 2006b). The ACT Math score is one of four variables loaded into the factor F4 Quantitative Skills. I was interested in extending this prediction research by considering F4 (Quantitative Skills) as a course placement indicator for the freshman engineering courses.

This section models placement into freshman engineering courses, independent of the overall model for first year GPA. Included in this placement modeling is a discussion of the AP (Advanced Placement) testing. The modeling of placement is included in this chapter because of its impact as a program on improved academic success of engineering freshmen.

5.5.1 Methodology

Placement tests are an integral part of the freshman orientation and first term course selection at Michigan. Each engineering student takes a math placement test and a chemistry placement test during freshman orientation. The math placement test is used to place a student either into pre-calculus (Math 105) or the first semester of calculus (Math 115). In addition, the AP math tests are used to place students into Calculus II (Math 116) and Calculus III (Math 215). The chemistry placement test is used to place a student into a remedial section of Chemistry 130 or a regular section of Chemistry 130.

Currently, math placement into Calculus I (Math) is based on the math placement test and the ACT/ SAT Math test scores. Because of the strong predictability of F4 for the first year GPA, I was interested in whether F4 (Quantitative Skills) could be used to place engineering students into their freshman classes.

A "C-"grade is usually considered as the lowest passing grade for the freshman courses. A linear regression was generated with the dependent variable being the course grade and the independent variable being the F4 (Quantitative Skills) factor score. The 90% predicted interval for a future value was calculated. The F4 (Quantitative Skills) value for the lower prediction interval for a course grade of 1.667 (C- on a 4-point scale) was determined from the regression line. This point was denoted by $F4_T$ and represented the lower bound (target) for F4 (Quantitative Skills) corresponding to a C- grade, taking into account statistical variation. Using this method, there is only a 5% chance that a future value of F4 (Quantitative Skills) would be less than $F4_T$.

Figure 5-10 shows an example using Chemistry 130. The F4 (Quantitative Skills) point on the lower 90% prediction interval corresponding to a "C- "grade is used as a target point ($F4_T$). $F4_T$ represents the minimal F4 (Quantitative Skills) score that a student would have and still be academically successful in this course (i.e. a grade of a C- or better)

In this analysis, the combined 2004 and 2005 cohorts ACT database was used. The letter grades were converted to a numeric score based on the 4.0 grading scale.

In developing this $F4_T$, the interest is in whether a value of F4 (Quantitative Skills) can be used for all freshman level courses. For different courses, the target for F4 (Quantitative Skills) would be different for each course. For the math courses, only the first time math course is considered. For example, only students who enrolled in Calculus II (Math 116) for their first Calculus course would be considered in the analysis of a value for the targeted F4(Quantitative Skills), $F4_T$. (The interest here is in placement into the first term math course.)

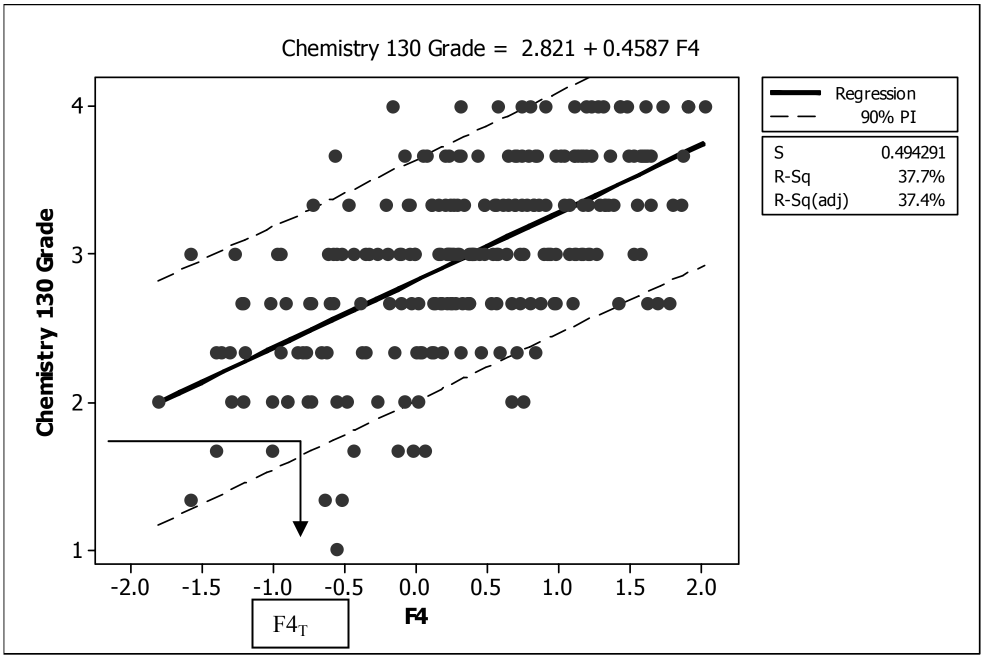

Figure 5-10: Illustration of $F4_T$ for Freshman Chemistry (Corresponding to a C- or 1.667 on a 4-point grading scale, sample size equals 240)

The current Michigan Engineering criteria for an AP placement into Math 116 and Math 215 were used (current in winter term 2007). These criteria include: a student must achieve a 4 or 5 on the AP Calculus AB test or 4 on the AP Calculus BC test in order to enroll in Math 116. For Math 215, a student must achieve a score of a 5 on the AP Calculus BC test (University of Michigan, 2007). Only the students who achieved these levels on the AP tests were included in the analysis of Math 116 and Math 215.

5.5.2 Results

Table 5-12 displays $F4_T$, the targeted F4 (Quantitative Skills) on the 90% lower prediction line in the regression between the course grade and F4 for a course grade of a "C-" or 1.667 on a 4.0 grading scale. This can be interpreted as follows: for a future student, if a student's F4 score is greater than $F4_T$, the student has a 95% probability of earning a C- or better. The $F4_T$ is a minimal threshold for placement into the course using the F4 values. Note that, for the math courses, the increase in the $F4_T$

corresponding to the sequencing of Calculus courses. The Pre-Calculus and Calculus II regressions yielded poor regression results. This is explored more in the Section 5.5.3 Discussion.

Table 5-12: Quantitative Skills $F4_T$ Values and Regression Results for Freshman Engineering Courses

Course	N	$F4_T$	Median F4	Adjusted R^2	Error Std Dev.
First Semester					
Pre Calculus Math 105	22	Regression not significant	- .90	0.0	N/A
Calculus I Math 115	117	-0.4	.25	.24	.554
Calculus II Math 116 (AP students)	89	0.0	.84	.06	.629
Calculus III Math 215 (AP students)	57	0.4	1.30	.32	.532
Chemistry I Chem 130	240	-0.7	.38	.37	.494
Second Semester or either Semester					
Engineering Physics Physics 140	228	0.3	.68	.24	.653
Introduction to Engineering Engineering 100	354	-2.0	.78	.10	.519
Programming Engineering 101	322	0.3	.72	.29	.722

The preparation level (as shown by $F4_T$) required for Chemistry 130 and Engineering 100 was minimal. The preparation level for Engineering Physics and Engineering 101 is equivalent to that of Calculus III.

Figure 5-11 clearly indicates the increasing progression of the average value of F4 for each calculus course.

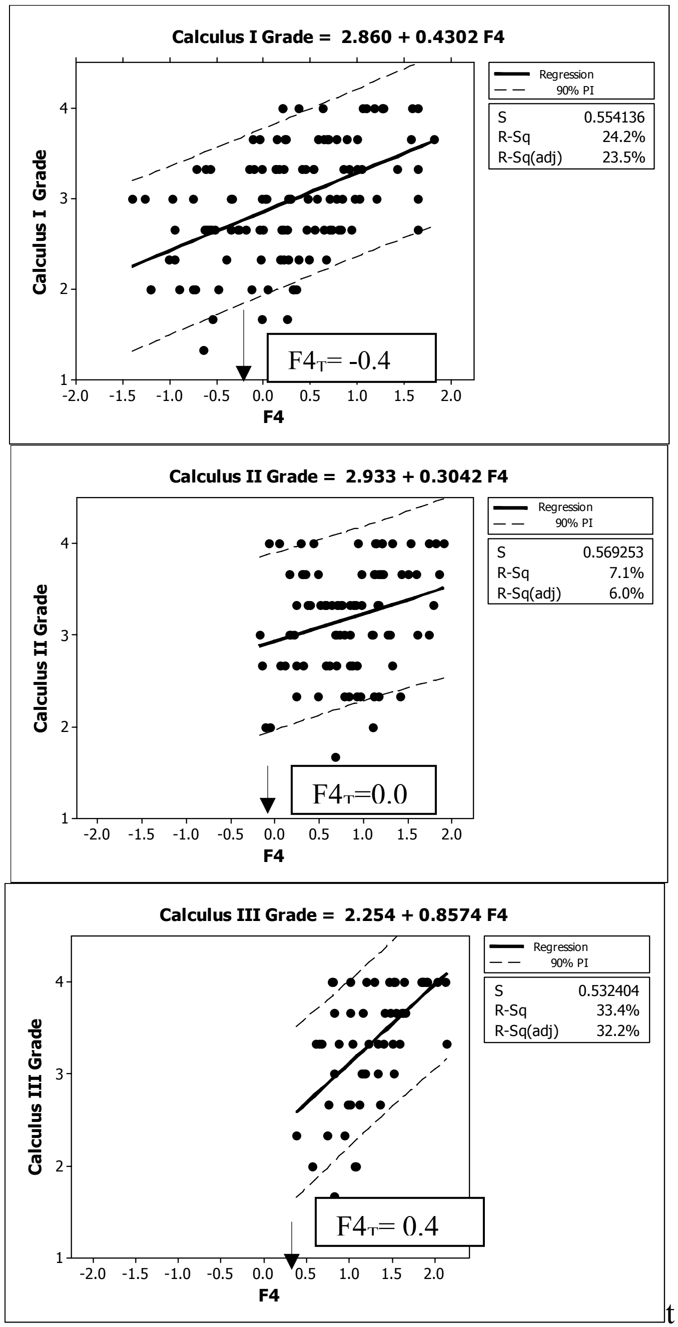

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Figure 5-11: Regression Plot of Math Course Grade Versus F4 (Quantitative Skills) for Calculus I top, Calculus II middle, and Calculus III bottom Show Increasing Progression of Minimal F4 (Quantitative Skills) Values. Sample sizes are displayed in Table 5-12.

Whereas close to the majority of the students who start in Calculus I have a F4 (Quantitative Skills) less than 0, for Calculus III, all the students have a F4 (Quantitative Skills) greater than 0.0. Figure 5-12 displays the empirical cumulative distribution of F4 (Quantitative Skills). The median of F4 (Quantitative Skills) is .78 with a range of -1.80 to 2.15.

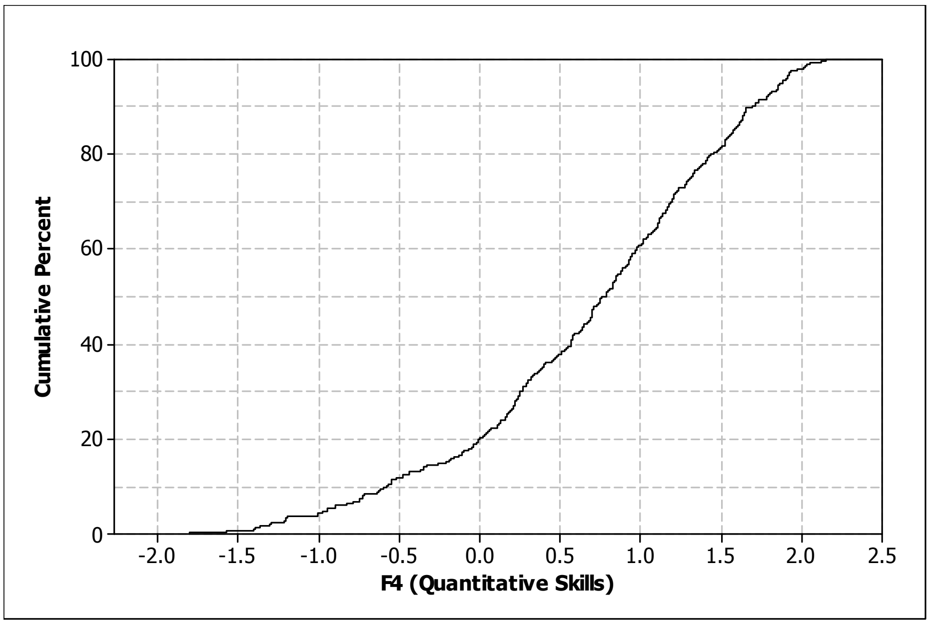


Figure 5-12: Empirical Cumulative Distribution of F4 (Quantitative Skills)for the Combined 2004 and 2005 Cohort Engineering Sector Sample (n= 361)

Based on Figure 5-12, Table 5-13 displays the percent of the engineering student sample with a F4 greater than $F4_T$ (i.e. are prepared for these courses from their high school preparation). For comparison to the combined sample of the four student sectors for both cohorts within the ACT subset, the overall median for all sectors is .16 with a range of -2.76 to 2.16. Approximately 22% of the engineering students have a F4 score less than the median of the overall student population.

Table 5-13: Percent of Engineering Students with a F4 (Quantitative Skills) Greater than $F4_T$

Course	$F4_T$	Percent of Engineering Students With $F4 > F4_T$
Math 115	-0.4	91%
Math 116	0.0	80%
Math 215	0.4	62%
Chemistry 130	-0.7	92%
Physics 140	0.3	67%
Engineering 100	-2.0	100%
Engineering 101	0.3	67%

5.5.3 Discussion

Research has shown that placement into the correct freshman courses for the first term on engineering is extremely important (Budny, 1998). F4 (Quantitative Skills) includes the loading of four variables: ACT math score, ACT science reasoning score, the U-M math placement test score and the U-M chemistry placement test score. F4 (Quantitative Skills) as a placement indicator was explored for three reasons:

- F4 (Quantitative Skills) has a stronger linear relationship with the course grade than the ACT Math score, as measured by the adjusted R^2.
- Of all the factor scores, F4 (Quantitative Skills) has the strongest linear relationship with the first year GPA.
- With the high science content in the Calculus courses, it is reasonable to assume that preparation in both mathematical knowledge and scientific reasoning is important as a predictor of success in the first semester engineering courses.

Quantitative Skills $F4_T$ can be viewed as an educational instrument for placement into the freshman courses taken by Michigan engineering freshmen.

The following findings are associated with the $F4_T$ values for the freshman engineering courses (refer to Table 5-12):

- An increase in $F4_T$ was evident from Calculus I through Calculus III. These courses were the first math course that the student placed into, either through the math placement test or AP tests. Furthermore, for the Calculus courses, the minimum F4 (Quantitative Skills) increases with each Calculus course in sequence.

- All the Pre-Calculus (Math 105) students had a negative F4 (Quantitative Skills) except for one student whose data is considered an outlier. In fact, all the Math 105 students had a F4 < -.4 (except the outlier). For Calculus I (Math 115), -0.4 is the $F4_T$ for the next course in the math sequence. This adds validity to using this instrument in placement practices.
- Chemistry 130 is a first semester course and showed a placement indicator of $F4_T$ = -0.7. Only 8% of the engineering students showed a F4 (Quantitative Skills) <-0.7. This suggests that the current assumed curriculum requirements for Chemistry 130 are aligned with the preparation level of the engineering freshmen, assuming that $F4_T$ is a valid placement indicator. Chemistry 130 is usually a first semester course. Since it has a $F4_T$ less than that of Calculus I (Math 115), all Calculus I (Math 115) and most Pre-Calculus (Math 105) students should be adequately prepared for Chemistry 130.
- Engineering 100 is an introduction to Engineering with different sections of Engineering 100 having a different project focus. It is designed for all levels of preparation of engineering students. With a $F4_T$ of -2.0, strong support is provided for Engineering 100 addressing the preparation levels of all engineering students.
- Physics 140 is almost always a second semester course for engineering freshmen. The pre-requisite for this course is that a student has completed Calculus I (Math 115). Physics 140 shows a $F4_T$ of 0.3, suggesting it requires a higher level of math and science reasoning than beginning Calculus II (Math 116) students. This suggests that an engineering student should be placed into Physics 140 only if he/she has completed Calculus II (Math 116) or entered as a freshman with a F4 (Quantitative Skills)> 0.3.
- Engineering 101 is a required programming course for engineering students. It is taken either in the first or second semester of the freshman year. As with Physics 140, Engineering 101 shows a $F4_T$ of 0.3. This suggests that engineering students

should enroll in Engineering 101 only after completing Calculus II or entering the freshman year with a F4(Quantitative Skills) > 0.3.

Review of Table 5-14 showed that F4 (Quantitative Skills) was not a significant predictor for the Pre-Calculus (Math 105) and minimally significant for Calculus II (Math 116). These two regressions were explored in more detail and are discussed in the next section.

Examination of the Pre-Calculus and Calculus II Regressions
Pre-Calculus

For the Pre-Calculus regression, the lack of significance was due to a small range for F4 with a relatively large amount of scatter in the Pre-Calculus Grade. Some of the students may have taken Pre-Calculus in the summer and some in the fall, contributing to this scatter. With a stepwise regression, it was found that F16 (Family Support), F8 (Choice of Major and Career), and F17 (Social Engagement-Socializing) were significant predictors. This warrants further investigation (see Table 5-14). This pattern is quite different than that for all students. Here the most significant predictor of academic success is F16 (Family Support), which is the combined education level of the student's parents. Second is a commitment to an engineering major and career(F8) , indicating the important of motivation. F17(Social Engagement- Socializing) is the third predictor, Its significance is at $p=.113$ instead of the standard .05 and is included as a possibly significant predictor. Missing as a predictor is F4(Quantitative Skills) or the factors from the P1 pillar (High School Academic Achievement). It appears that the probable commitment by parents (and their encouragement) and motivation towards an engineering major are the leading predictors for a high grade in Pre-Calculus.

Table 5-14: Stepwise Regression Results of the Pre-Calculus Grade with the Factors as Predictors (n=22)

Predictor/Step	Regression Coefficient	T	P	Adjusted R^2	Final Mallow's Cp
Constant	2.247				
F16 (Family Support	0.203	2.53	0.021	0.133	1.6
F8 (Choice of Major and Career	-0.211	-2.38	0.028	0.311	-1.2
F17(Social Engagement-Socializing	0.190	1.66	0.113	0.370	-1.2

Calculus II

Because of the low R^2 for the regression of the Calculus II course grade versus F4 (Quantitative Skills), a stratification problem was suspected with preparation levels, due to the high school AP Calculus courses and measured by the AP Calculus test scores. To take Calculus II as their first math course in the freshman year, engineering students either scored a 4 or a 5 on the AP Calculus AB test or a 4 on the AP Calculus BC test. The analysis of this data supports that students who scored a 4 on the (AP Calculus) AB test should be considered as a less prepared group of students (on the average) for Calculus II (Math 116) than the students who scored a 5 on the AB test or a 4 on the BC test. The following statistics are noted.

- First, the F4 (Quantitative Skills) box plot distributions were reviewed by AP test score (see Figure 5-13). The median for F4 (Quantitative Skills) is substantially different for these three groups, with the students who scored a 4 for the Calculus AB test having the smallest values for F4. Since F4 is the independent variable, this could lead to a low predictability if all three groups are combined in one regression.

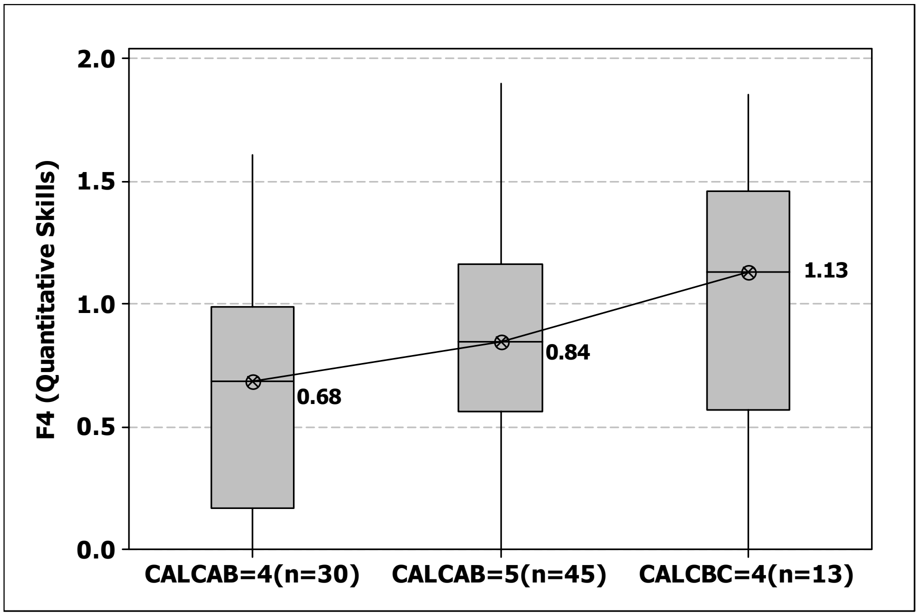


Figure 5-13 : Box Plots of F4 by AP Test Score for Students Enrolled in Calculus II

- When a regression is run for each group, the difference is more evident. The regression line of AP Calculus AB=4 students has a lower intercept than that of the other two groups (See Figure 5-14).

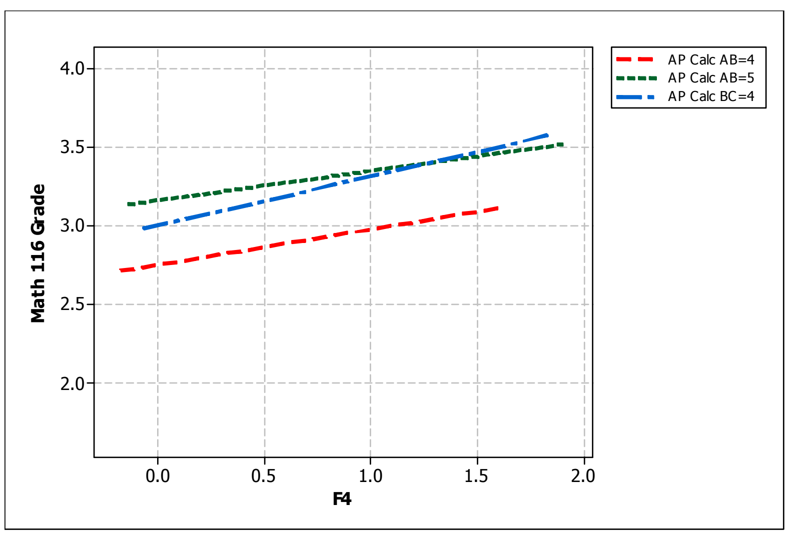


Figure 5-14: Regression Lines of the Math 116 Grade versus F4 Show a Significantly Lower Predicted Math 116 Grades for AP Calculus AB Students with a Score of 4

- As further evidence of a potential preparation problem for Calculus II students who scored a 4 on the AP Calculus AB test, the cumulative distributions of the Calculus II grade were plotted (see Figure 5-15). The Kruskal-Wallis test showed a significant difference in the cumulative distribution of the Calculus II course grade for the students who scored a 4 on the AP Calculus AB test compared to the students, who scored a 5 on the AP Calculus AB test (p=.002).

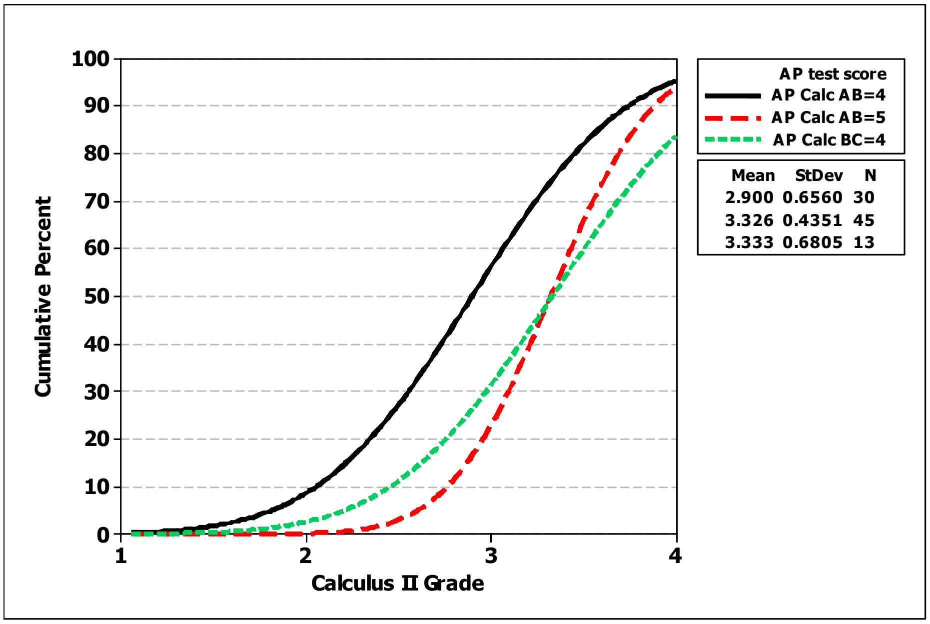


Figure 5-15: Cumulative Distributions of for the Math 116 Students Show Differences by AP Test Score

These findings suggest that the stratification of the data by AP test score accounts for the low R^2 for the Calculus II regression. Placement of students who scored a 4 on the AP Calculus AB test needs further research and consideration as a placement policy.

5.6 Summary and Recommendations

The education model developed in Chapter II for engineering academic success was mostly validated. To measure the predictability of the ACT admission scores versus the SAT admission scores, two subsets were developed; an ACT subset and an SAT subset. Based on the regression analyses in this chapter, the ACT test scores were determined to have a better predictability and therefore the ACT subset was selected for further analysis. A**ll the summary statements made in this section are based on the ACT subset.**

5.6.1 Modeling of First Year GPA

Of the nine pillars, the following were found to contribute significantly to first year academic success (GPA):

- P1 High School Academic Achievement
- P2 Quantitative Skills
- P4 Commitment to Career and Educational Goals
- P5 Confidence in Quantitative Skills
- P7 Financial Needs
- P8 Family Support

P3(Study Habits), P6 (Commitment to this College) and P9(Social Engagement) each explained less than 1% of the total variation with their pillar (Table 5-1). P3 (Study Habits) had the most literature support. Included in P6 (Commitment to this College), was a variable that indicated if Michigan was the first choice college. Its non-significance suggests that motivation to attend Michigan was not sufficient for academic success.. P9 (Social Engagement) was also not significant.

Prediction modeling of the first year GPA with regression analysis showed that the following factors and their associated pre-college characteristics contributed to the explanation of the variation in first year GPA.

- F4 (Quantitative Skills) – this included both knowledge of mathematics and scientific reasoning. Four variables were loaded on this factor: the ACT math score, the ACT science reasoning score, the University of Michigan math placement test and the University of Michigan chemistry placement test.
- F1 (High School Grades)- this included the high school GPA and rank
- F11(Confidence in Quantitative Skills)- this included two CIRP variables; self-rating of math ability and self-rating of computer ability

- F10 (Career Goals) - three CIRP variables were highly loaded on this factor; they were the subjective importance of going to college to “get training for a specific career”, “to be able to make money”, and “to prepare for Graduate/Prof school”.

In addition, the interaction between F1 (High School Grades) x F4 (Quantitative Skills) was strongly significant. It was found that the interaction explained 6% more variation in the first year GPA beyond what the F1 (High School Grades) and F4 (Quantitative Skills) explained. (See Section 5.2.3 for the prediction equations.)

These factors (equation 5.2) explained closed to 40% of the total variation in first year academic success (GPA) for engineering students at Michigan. All of these factors are based on high school preparation and pre-college characteristics. Although each student was influenced by his/her experiences at college (Tinto, 1993), it is clear that the preparation and pre-college attitudes and confidence are major contributors to success in the first year of engineering.

The significance of F1 (High School Grades) and F4 (Quantitative Skills) was consistent with engineering academic success empirical studies and was expected. The significance of F11 (Confidence in Quantitative Skills) was consistent with a study by Besterfield et al. (2002). This study showed that confidence in engineering skills from the PFEAS© survey was a significant predictor for whether a student was placed on academic probation after the first semester of engineering. It is worth noting that F1 (High School Grades) based on the high school GPA and rank is more significant than F2 (High School Performance), which is based on the ACT Composite score.

The prediction modeling results were generally consistent with the Besterfield-Sacre et al. (1997) study for predicting first term GPA at the University of Pittsburgh. In that study having a scholarship, high school rank and SAT Math were the first three predictors in a stepwise regression. The significance of F4 (Quantitative Skills) and F1 (High School Grades) was consistent with Besterfield-Sacre’s predictors of high school rank and SAT Math. Scholarship information was not considered in this study. Levin and

Wyckoff (1988) at Penn State University showed that high school GPA and SAT Math to be the first two predictors in a stepwise regression on first year GPA in engineering. They also found the math placement test and chemistry placement test to be a significant predictors (consistent with this study's F4 (Quantitative Skills). Both the Besterfield-Sacre study and the Levin and Wyckoff studies showed a study habits predictor, which was not prevalent in this study. Besterfield-Sacre's study also showed that "like math/science" was a significant predictor; this is similar this study's Confidence in Quantitative Skills which is based on self-ratings of math and computer abilities. The prediction results in this study were also consistent with French et al. (2003), who found that the SAT Math, and High School Rank were among the significant predictors of college GPA.

This modeling strongly suggests that motivation cannot overcome a lack of preparation in academic skills. If this were the case, other factors would have been more significant. F4 (Quantitative Skills), by itself, accounts for 23% of the total variation in first year GPA. The implication for support programs is that engineering students will benefit more from strong tutoring programs that develop preparation levels than from social support groups. This may not be true for all student groups.

The model was validated by applying it to an independent sample from a different year. The validation results showed the same level of predictiveness using the adjusted $R^{2,}$ verifying that equation 5.2 can be extended to more than one year and that close to 40% of the first year GPA can be explained by pre-college characteristics.

5.6.2 Gender and Ethnicity Differences for Academic Success

Academically, female students succeed at the same level as male students in the freshman year. No significant difference between female and male students was evident for the average of first year GPA. There was a statistically significant difference in the average F4 (lower average for female students for Quantitative Skills) and average F11 (lower Confidence in quantitative skills for female students) at p=.000. There was not a significant difference in F1 (High School grades). This suggests that programs such as

WISE (Women in Science and Engineering) help female students overcome a lower quantitative skill and a lower confidence in those skills in order to achieve academic success (GPA).

Academically, under-represented minorities achieve at a significantly lower average first year GPA than non-under-represented minorities. Once the significant predictive factors (F1 [High School Grade], F4 [Quantitative Skills], F10 [Career Goals], and F11 [Confidence in Quantitative Skills]) are entered into a linear model with ethnicity, no significant difference exists between the adjusted average first year GPA of URM students compared to Non-URM students.

In order to achieve more racial diversity, the University of Michigan has had a policy of considering race in its admissions criteria. So a significant difference would be expected, assuming that the first year GPA is affected by academic preparation levels. The model strongly validates the importance of preparation levels both in general academic preparation and preparation in quantitative skills. The data supported that a statistically significant difference in the average of both F1 (High School Grades) and F4 (Quantitative Skills) existed between URM and Non-URM students. Consistent with the model, these differences accounted for the statistically significant lower average first year GPA of under-represented minorities compared to majority students.

What is extremely significant here, is that when the average first year GPA of URM students was adjusted to the average F1 (High School Academic Achievement), F4 (Quantitative Skills), F10 (Career Goals) and F11 (Confidence in Quantitative Skills), there was no significant difference in the first year GPA between URM students and Non-URM students.. In other words, these four predictors explained the average difference in first year GPA between URM and Non-URM students. Although there may have been cultural differences between under-represented students and non-under-represented (majority) students, they did not play a significant role in the difference of these two student groups for first year academic success. If this were the case, there would have been a significant difference after F1 (High School Grades), F4 (Quantitative

Skills), F10 (Career Goals) and F11 (Confidence in Quantitative Skills) were taken into account. It is appropriate to note that URM students averaged a significantly higher F10 (Career Goals). This was interpreted that, on the average, URM students were more motivated towards an engineering career. Based on the model, in the competitive grade environment of Michigan, *on the average*, this motivation cannot overcome less preparedness in math and high school college-preparation courses. On an individual student basis, there may be exceptions.

The modeling of engineering academic success was first constructed to consider pre-college characteristics without considering gender or ethnicity. Once the significant pre-college characteristics were selected using the factor scores, it was shown that when these pre-college characteristics are taken into account, there is no significant difference in gender or ethnicity. This provides support for this model for academic success that is independent of gender and ethnicity.

5.6.3 Advanced Techniques for Intervention Analysis

Two advanced techniques were used to explore first year engineering success. The Hotelling's T^2 was found to be successful as a multivariate tool and showed stability among the students' data. Some outliers were identified. It is recommended that the Hotelling's T^2 method be further explored as a research tool for engineering retention studies.

The Randomized Database Method was used to randomly select students' records from the database in order to minimize the confounding effects of a student participating in more than one intervention program. The results using this method were considered effective in analyzing whether an enrollment in Engineering 110 (careers in engineering) and a higher frequency of visits to the Engineering Advising Center affected the first year GPA. For example, a group of students enrolled in Engineering 110 could also participate in a learning community or mentoring program. By selecting records randomly from the database, this bias was minimized. This method showed promise in this research and its use is recommended.

5.6.4 Intervention Programs

In this chapter, three intervention programs were evaluated with respect to first year academic success (GPA). In summary, the conclusions were:

- The AMP mentoring program of supporting second-semester students who achieved a low first-semester GPA demonstrated success. The improvement of the second semester GPA of the mentored students over the control group was statistically significant with the mentored students achieving a one-grade improvement in the GPA over the first semester GPA. It is recommended that this mentoring program be continued.
- No significant difference in average GPA was evident between the students with a high frequency of advising and a low frequency of advising. Since the students with lower GPAs visit the advising center more often, this result suggests that the EAC is highly effective in helping students become academically successful.
- Enrollment in Engineering 110 did not have a significant effect on the first year GPA. Engineering 110 can be thought of as an intervention to motivate students' commitment to engineering. The non-significance of Engineering 110 in predicting the first year GPA is consistent with the literature review (Chapter II), which showed that commitment to career and educational goals is a significant predictor more for retention than for academic success. There were two significant interactions associated with Engineering 110: Engineering 110 x Gender and Engineering 110 x Advising Frequency. More confirmatory research is recommended to further study these interactions. In particular, it is recommended that a survey on Engineering 110 students be conducted on their congruence to engineering interests (similar to the measure that Leuwerke et al. used) before and after completion of Engineering 110.

5.6.5 F4 (Quantitative Skills) as a Placement Indicator into Freshman Courses

Because of the significance of proper placement into the freshman level courses for student academic success and because F4 (Quantitative Skills) was the most significant factor for first year GPA, modeling of the freshman level course grades using F4(Quantitative Skills) was conducted.

F4 (Quantitative Skills) is the factor associated with quantitative skills and explained 23% of the total variation in first year GPA. Four variables are loaded on F4: the ACT Math score, the ACT science reasoning score, the U-M math placement test score and the U-M chemistry placement test score. A F4 equivalent to a minimal value for expected success in a course was developed and was denoted by $F4_T$. The values for each course are shown in Table 5-12. The results were very consistent; further research in using F4 (Quantitative Skills) is recommended. Because F4 (Quantitative Skills) was the best predictor of first year GPA for the entire database, it was expected that it would be a significant predictor for each subset of data associated with the first math course. For Pre-Calculus and Calculus II, this was not the case. F4 (Quantitative Skills) was not a significant predictor for first year GPA for students who enrolled in Pre-Calculus; the range of F4 (Quantitative Skills) was relatively small. F4 (Quantitative Skills) was significant for predicting first year GPA for students who AP into Calculus II, but only with an R^2 of 6%. Further analysis showed that students who scored a 4 on the AP Calculus AB test earned a significantly lower average course GPA than students who score a 5 on the AP Calculus AB test or a 4 on the AP Calculus BC test. It was recommended that students in the first group should be selected for a special section of Calculus II. Minimally, it is recommended that the College of Engineering placement policy be reviewed with respect to placement of AP Calculus students.

5.6.6 Summary

In summary, the modeling of first year GPA was highly successful and supported previous research that showed the importance of quantitative skills and the high school preparation for college-level courses. With the use of factor analysis, 38% of the total variation in first year GPA was explained to be related to pre-college characteristics. Significantly, this research compared the ACT data to the SAT data and concluded that the ACT data gave similar results as the SAT data for the 2004 cohort, and the ACT gave a better prediction for the cross-validation sample. This is one of the few engineering education empirical studies that use the ACT scores for prediction. This study also showed a strong interaction between quantitative skills and overall high school grade performance. Including the interaction in the model contributed to a higher R^2. Confidence in quantitative skills was also shown to be significant. There was no difference in gender or ethnicity for academic success (GPA), once the significant covariates in the model were controlled (adjusted).

With respect to interventions for student academic success, two findings were particularly significant.

1) Mentoring of students at risk in the second semester showed significant improvement in the first year GPA.

2) A combination of a high level of advising and enrollment in Engineering 110 showed substantial improvement in the first year GPA over students who only participated in a high level of advising visits.

Further confirmatory research of these two findings is recommended.

CHAPTER VI
MODELING OF STUDENT RETENTION FOR THE ENGINEERING STUDENT SECTOR

This chapter will discuss the modeling of both college and university retention for engineering students using logistic regression. The following topics are included in this chapter:

- Validating that the first year GPA is a strong predictor of retention (Section 6.1)
- Modeling retention with the pre-college characteristics (Section 6.2)
- Sensitivity analysis of retention (Sections 6.2.2.2 and 6.2.3.2)
- Gender and ethnic differences with respect to retention (Section 6.2.4)
- The influence of initial commitment to engineering and the University of Michigan on retention (Section 6.3)
- Effect of advising frequency and enrollment in Engineering 110 on retention (Section 6.4)
- The summary includes a discussion of why Michigan Engineering has a high retention rate (Section 6.5)

In the model (see Figure 6-1, Section 6.1), it was hypothesized that the first year GPA would be a strong predictor of both college and university retention. The results showed that the GPA was not a predictor of college retention. The pre-college characteristics were then explored as possible predictors of college and university retention. A sensitivity analysis was conducted on the significant variables and their relationship to the retention rate. Next, the question of whether freshman engineering retention varies by gender or ethnicity was explored.

A review of the literature showed that there is literature-based evidence that students that have a high rating of "general impression of engineering" have a higher retention rate (Besterfield-Sacre, et al., 1997). The research of Leuwerke et al. (2004) supports that career congruence in engineering influences freshman engineering retention. In addition, Watson and Froyd (2007) proposed that career development in engineering needs to be developed throughout a student's undergraduate student experience. In this chapter, enrollment in Engineering 110 in addition to advising frequency will be explored for effectiveness in ***retaining students in engineerin**g*. If, as the model (Figure 6.1) suggests, that a revised commitment to engineering is important, then students who enrolled in Engineering 110 should have a higher retention rate than students who did not take Engineering 110. This will be verified.

Section 6.1 discusses the effect of first year GPA on college and university retention of engineering students. Section 6.2 discusses the effect of the pre-college characteristics on college and university retention. Section 6.3 discusses whether there is a relationship between the initial commitment to an engineering major/career or choice of college and the college and university retention. Section 6.4 discusses the contribution of enrollment in Engineering 110 and the level of advising to engineering retention. Finally, Section 6.5 includes the summary and recommendations.

6.1 Validation on the Influence of the First Year GPA on Retention

This section discusses the modeling of retention using the first year GPA. For purposes of discussion, Figure 6-1 displays the retention decision in more detail. According to this model, the retention of students in engineering is dependent on three factors:

1) Level of student success (first year GPA)

2) A revised commitment to engineering

2) A revised commitment to the college

An engineering retention model will be developed with the level of student success (first year GPA) as an input. Because of limitations of the data used in this research, only the first year GPA (of the three factors listed above) is measured and discussed in this research.

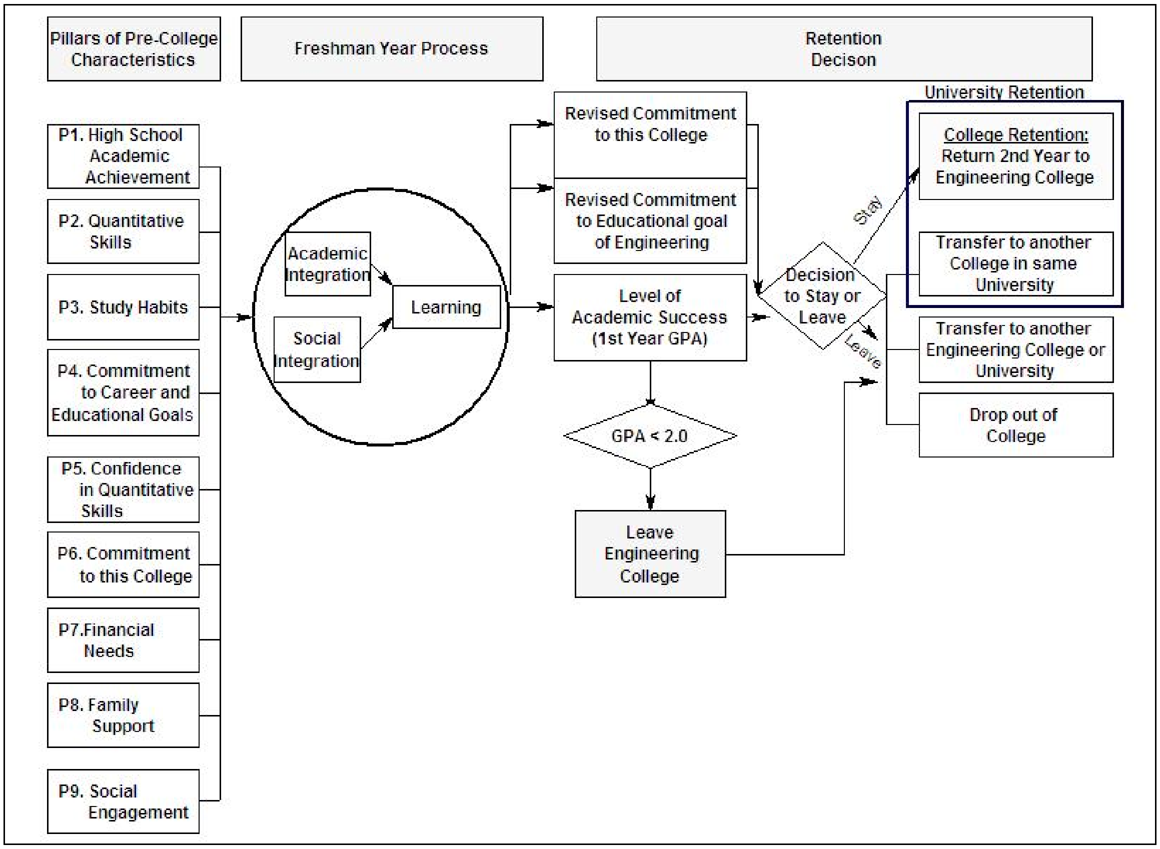


Figure 6-1: Student Success Model

6.1.1 Methodology

Definitions

In discussing retention of engineering students, there are two definitions for student retention.

- **College retention**: the Percent of students who matriculated into the College of Engineering and continued in a major in engineering at Michigan for the third semester (fall semester of the second year). In Figure 6-1, the college retention box indicates the students who stay in engineering.

- **University retention**: the Percent of students who matriculated into the College of Engineering and were enrolled in a program at Michigan for the third semester (fall semester of the second year). In this definition, students who transferred to another college at Michigan are considered retained in the university. In Figure 6-1, the larger box represents the students who are counted in this statistic. The drop-out rate from a university is 100- (the university retention) and includes students who transferred to another engineering college or university.

Modeling with Logistic Regression

In modeling student retention, logistic regression is the most common technique used in the research literature (Besterfield-Sacre et al., 1997, French, et al., 2005). This section summarizes the use of logistic regression and compares it to the regression used in Chapter V.

In Chapter V, ordinary least squares regression was used to develop a model for the first year GPA. The first year GPA, as a dependent variable in the regression, is a continuous variable. The factors for the pre-college characteristics were the independent variables. In ordinary least squares regression, it is assumed that the errors are normally distributed with a mean of 0 and a constant standard deviation.

In this chapter, logistic regression will be used to model student retention. Retention for an individual student is a dichotomous variable; either he or she returned to engineering or left engineering. The dependent variable, therefore, is usually coded as a “0” or “1”. The independent variable is the first year GPA. From this model, the error in the logistic model for retention is distributed as a binomial distribution. The parameters of the logistic regression model are estimated using maximum likelihood instead of least squares methods.

Suppose a logistic regression model is desired with retention modeled in terms of the first year GPA. A logistic regression model is given by:

$$Y_i = \ln (P_i / (1-P_i)) = \beta_0 + \beta_1 X_i + \varepsilon_i \qquad 6.1$$

Where

Y_i = 1 if student i registered for the second year (student retention); 0 if student i did not register for second year (student not retained)

P_i = probability of an engineering student returning to engineering for the 2nd year of engineering college

X_i = first year GPA for ith student

The predicted first year retention probability can be calculated as:

$$P_i = \exp (b_0 + b_1 X_i) / (1 + \exp (b_0 + b_1 X_i) \qquad 6.2$$

Where the coefficients b_0 and b_1 are the estimates of β_0 and β_1.

(Hosmer and Lemeshow, 2000)

Note that if Y_i were coded as a "0" to represent a student who registered for classes in the second year, the P_i represents the probability of attrition.

In the engineering education literature, the logistic model is usually used for retention studies. It can be argued whether the logistic or probit model is a better theoretical model. Because it is expected to have higher probability of retention for higher levels of the first year GPA, it could even be argued that the complementary log log model should be considered. In this research, the use of the probit model and the complementary log log gave similar results to the logistic model. Because the logistic model is commonly used in retention research, the logistic model was used for this analysis.

Goodness of Fit

The Hosmer-Lemeshow (H-L) goodness of fit test is commonly used to determine the goodness of fit of the data to the logistic model. Xie et al (2007) states that the objective of a goodness of fit test is "to reflect whether the predicted values are an accurate representation of the observed values. Omitted predictors, a misspecified form of the predictor, or an inappropriate link function can all result in poor prediction." Researchers are interested in a better-performing goodness of fit test, and especially in improving the power of the test, in detecting missing terms or an incorrectly specified model. In this section, three goodness of fit test statistics are discussed: the Pearson chi-square, the H-L test, which is also known as the Ĉ test, and the unweighted sum of squares statistic , known as the Ŝ test. (Other proposals for goodness-of-fit tests for logistic regression have appeared in the research literature, including Hosmer, et al. (1997), Hosmer and Hjort (2002), Pigeon and Heyse (1999) and Xie et al. (2007).)

Historically, before the development of the H-L statistic, the Pearson chi-square test was used where equal intervals were defined in terms of the independent variable, rather than in terms of the dependent variable. The H-L test statistic, as developed by Hosmer and Lemeshow, uses the chi-square test statistic similar to a chi-square statistic, except each category has an equal estimated probability. Instead of partitioning the data by equal intervals of the x- variable (i.e. the Pearson chi-square test), the data is partitioned based on equal intervals by the empirical probability of occurrence. The H-L test statistic uses a 10 x 2 contingency table, where the 10 bins of equal sample size are often referred to as the "deciles of risk" (Hosmer, et al., 2000). For each bin, there are two cells, one will represent the frequency of the attribute being studied (with a data value of "1" and the other will be the frequency of the attribute not being present (with a data value of "0"). In the case of a retention study, the first cell will include the number of students who returned to college and the second cell will include the number of students who dropped out. It is also referred to as the Ĉ statistic:

$$\hat{C} = \sum_{k} (O_k - n_k \overline{P}_k)^2 / n_k \overline{P}_k (1- \overline{P}_k)$$

where O_k is the observed frequency for the kth bin, n_k is the observed sample size for the kth bin and $\overline{P}_k$ is the average expected probability for all observations in the kth bin.

The unweighted sum of squares statistic, $\hat{S}$, is the sum of squared residuals and is calculated by:

$$\hat{S} = \sum_{i=1}^{i=n} (Y_i - P_i)^2$$

for all data. (Hosmer and Hjort, 2002).

A disadvantage of the Pearson chi-square goodness of fit test was that it required an expected frequency of at least 5 in each cell in order to use the chi-square distribution for significance testing. In most cases, especially with sample sizes of 200 or less, the expected frequency could be less than 5 for the outer cells.

The H-L test, as a reliable statistic, has two areas of major concern. The first concern is directly related to the algorithm used by statistical software packages. The concern is that the statistic and associated significance level are different for different software packages with the same data. (Hosmer et al., 1997; Pigeon and Heyse, 1999; Harrell, 2001) This is due to the handling of ties and the establishment of the cutpoints needed for the H-L test. For example, if the independent variable is GPA, which has an underlying continuum, that continuum must be partitioned into ten bins. The endpoints of the bins are known as the cutpoints and may be slightly different from one statistical package to another. In one statistical package, the H-L statistic could indicate significance and in the other non-significance. The second issue is defined as follows. The dependent variable is a dichotomous 0-1 variable. If a student is retained, the dependent variable may be coded as a "1" and then the logistic regression predicts probability of retention. As an alternative method, the coding of a student who is retained could be indicated by a "0" (where "1" is coded for students not retained). In comparing these two methods of coding of the data, the coefficients of the logistic regression have the same magnitude but the signs are opposite. This makes sense, since in the first case, the probability of retention is predicted and in the second case, the probability of attrition is predicted. The concern is that the H-L goodness of fit statistic with the same software is different. This is due to the cutpoints being different, especially if the total sample size is not a multiple of ten. The last interval usually has the smallest frequency.

Another issue is the expected frequency within a cell. The H-L test, as specified, has 20 (2 x 10) cells. First, the total sample size is divided by 10, and then the frequencies are divided into the observed frequencies of a "1" and of a "0" representing the attribute being considered (in this case, retention of students). For example, if the total sample size were 500, each "decile" or bin of two cells would have a frequency of 50. In each of the two cells would be the frequency of a "0" and of a"1," respectively, adding to 50. The expected value for each of these frequencies would also be calculated. It is possible in the outer cells, for there to be a small expected value for either a "0" or "1," representing the tails of the distribution. Since the H-L test is distributed approximately as a chi-square (Hosmer and Lemeshow, 2000; Pigeon and Heyse, 1999), the usual concern about an expected frequency of at least a frequency of 5 for each cell is applicable.

The unweighted sum of squares, $\hat{S}$, was first proposed by Copas (1989) for categorical data. Its advantage is that for a continuous x variable, cutpoints do not need to be used and a large residual in the tail of the distribution have less influence on the statistic than with the H-L statistic. It has the disadvantage of not identifying individual residuals that may contribute to a high $\hat{S}$ value. There is substantial interest in the research literature in this statistic (Hosmer, et. al., 1997, Harrell, 1999; Hosmer and Hjort, 2002)

One of the issues among statisticians is the use of cutpoints, as one would use in a chi-square test. If the independent variable in a logistic regression has an underlying continuum (e.g. GPA, high school rank), the selection of cutpoints can influence the significance of the test (Harrell, 2007). Some of the recent goodness of fit tests have tried to address this concern. In particular, there is interest in the research literature in the unweighted sum of squares test, S. (Harrell, 1999; Hosmer, et al., 1997)

Hosmer et al. (1997) reviewed the work of Copas on an unweighted sum of squares and conducted an extensive simulation study to compare logistic regression goodness of fit tests. Hosmer and Hjort (2002) conducted another simulation study to compare the goodness of fit statistics with respect to the power of the test and this will be discussed next.

Consistent among the three goodness of fit tests, is that the simulations confirm a significance level of about 0.05 when the statistic is used under the null hypothesis of no difference (i.e. the simulated results are from a logistic distribution). The probability of rejecting the test with a critical value set at a significance level of 0.05 ranged from 0.032 to 0.068 for 500 simulations. Therefore, it can be concluded that all three test statistics have a correct test size and have a minimal type I error.

In addition, Hosmer and Hjort (2002) looked at the power of these three tests for three conditions:

1. The detection of a quadratic term in the correct model when it is not in the model to which the data is fitted
2. The detection of an interaction between a continuous independent variable and a dichotomous independent variable when it is not in the model to which the data is fitted
3. The detection of an inappropriate underlying distribution. The data is fitted to a logistic model. The alternative distributions considered for a power evaluation of the goodness of fit test were the probit, complementary log-log, the logistic model with longer or shorter tails and an asymmetric logistic model with one tail longer and the other tail shorter.

The findings from the simulations in the Hosmer and Hjort (2002) paper are discussed next.

1. **Detection of a quadratic term.** With an increased quadratic effect and increased sample size, the power to detect the quadratic effect increased. All three tests yielded the same magnitude of power. For a sample size of 100 and a large

quadratic effect, the power from the simulations was greater than .90 for all three tests. For a sample size of 500, the power was at least .80 for even a small to moderate quadratic effect for all three tests. The power calculations were consistent for all tests.

2. **Detention of an interaction term.** With a sample size of 100, all three tests performed poorly with respect to rejecting the model when an interaction term was present. With a large sample size of 500, the simulated power of the test for all three tests was varied with .050 for a low interaction effect to .986 for a high interaction effect. The Pearson chi-square and the $\hat{S}$ test outperformed the $\hat{C}$ test for power across the spectrum of levels of interaction effect. Except for the highest level of interaction, the power was not as high as would be desired.
3. **Detection of an inappropriate underlying distribution.** When the sample size was 100, the power was poor for all three tests. The power was improved for a sample size of 500. The $\hat{S}$ test outperformed the other two tests. Only in the case of an asymmetric tails, was the power greater than .80 for all three tests. The power of the unweighted sum of squared residuals test ($\hat{S}$) was .77 for the logistic model with short tails. This indicates that the $\hat{S}$ test detects this condition much better than the other two tests, which showed a power of .436 for the chi-square and .190 for the $\hat{C}$ test. Table 6-1 displays the power probabilities for a sample size of 500 from these three tests.

Table 6-1: Simulated Power for alternative underlying distributions with n= 500

Underlying Distribution	**Pearson's Chi-Square**	**H-L Test $\hat{C}$**	**Unweighted Sum of Squares, $\hat{S}$**
Probit	.076	.068	.102
Complimentary log-log	.176	.270	.234
Logistic model with long tails	.130	.078	.126
Logistic model with short tails	.436	.190	.772
Logistic model with one long tail and one short tail	.872	.926	.864

Source: Hosmer and Hjort (2002)

Except for the asymmetric tail, and the short tail logistic model for the $\hat{S}$ test, the simulations support a concern that these tests do not detect an incorrect model (such as a probit or complimentary log-log) even with a large sample size. Relative to the three test considered in this discussion, Hosmer and Hjort (2002) recommend using the Pearson chi-square and unweighted sum of squared residuals, $\hat{S}$, in addition to the H-L goodness of fit test, $\hat{C}$. In addition, they recommend reviewing the 2 x 10 table of observed and expected frequencies.

In their book, *Applied Logistic Regression,* Hosmer and Lemeshow (2000) discuss the statistical issues faced by the researcher in using the H-L goodness of fit test, $\hat{C}$, and the unweighted sum of squared residuals, $\hat{S}$. They discuss the validity of the H-L goodness of fit test, $\hat{C}$, being dependent on an expected frequency of about 5.. Some researchers require an expected frequency of at least 5 for each cell; Hosmer and Lemeshow indicate, "we feel that there is reason to believe that the calculation of the p-value is accurate enough to support the hypothesis that the model fits." They caution against collapsing bins to satisfy the expected frequency of 5 criteria. If the 10 groups in the H-L goodness of fit test are collapsed down to less than 6 groups to merge cells so that the expected frequency is about 5, the test "will almost always indicate that the model fits." (Hosmer and Lemeshow, 2000). Contrary to this, Pigeon and Heyse (1999) provided an example where they collapsed the number of bins down to 4 bins because their sample size was only 39, and had a significant $\hat{C}$ statistic ($p<.05$). Hosmer and Lemeshow indicate that the advantage of $\hat{S}$ is that it is simple to use; its disadvantage is that without using a table of observed versus expected frequencies, an important residual may be missed. Therefore, they recommend that diagnostic plots and the contingency table also be used to evaluate residuals.

The following summary provides the algorithms for the calculation of the p-value for each test. The Pearson chi-square test is well known and its statistical significance is based on the chi-square distribution.

$$X^2 = \Sigma[(O_i - E_i)^2 / E]$$

The Pearson chi-square test is calculated using Minitab 15.0. The H-L goodness of fit test is also based on a chi-square distribution with 8 degrees of freedom. It is calculated by both SPSS 15.0 and Minitab 15.0. The $\hat{S}$ statistic has approximately a normal distribution. If the expected probability of retention is denoted by P_i, and $v_i = P_i (1- P_i)$, then V, the sum of the $v_{i,}$

$$V = \sum v_i$$

is the mean for the distribution of $\hat{S}$. The variance for the distribution of $\hat{S}$ is calculated by first computing the weighted linear regression of $(1\text{-}2\ P_i)$ on the X-variables of the logistic regression with weights, v_i. The estimate of the residual sum of squares, *RSS*, from this regression is the estimated variance of the approximate normal distribution of $\hat{S}$. (Hosmer and Hjort, 2002). Significance level can be calculated with a Z-score with a mean of V and a standard deviation of the square root of the residual sum of squares from the weighted regression. SPSS stores the residuals of the $Y_i - P_{i.}$. From these residuals, the S statistic may be calculated. Then the mean and standard deviation may be calculated with the weighted regression, which is available in SPSS. Using a Z-score of $Z = (\hat{S} - V)/\sqrt{RSS}$ the level of significance, p, can be calculated from a Normal Distribution table.

Sample Size Considerations Require Combining of Two Cohorts

The initial design of this research included two data subsets: the first to estimate the parameters of the model; the second to independently validate the model with a high degree of predictability. This approach was used in modeling first year student success (GPA) in Chapter V. The 2004 cohort was used to model student success and the 2005 cohort was used to validate the model.

With the very high college retention of 93.9% in the combined 2004 and 2005 cohort, the sample of students who choose to leave engineering is small for each cohort. In this sample of 735 engineering students for the two cohorts, 21 students in the 2004 cohort and 24 students in the 2005 cohort choose to leave engineering.

This is an excellent university situation in the retention of students, but provides major challenges to modeling of retention. Hosmer and Lemeshow (2000) discuss using a guideline of 10 observations per estimated parameter in the smaller group for a logistic regression. Peduzzi, Concato, Kemper, Holford and Feinstein (1996) developed this guideline based on their research. According to Hosmer and Lemeshow,

> " Peduzzi et al. show that a minimum of 10 events per parameter are needed to avoid problems of over estimated and under estimated variances and thus poor coverage of Wald-based confidence intervals and Wald tests of coefficients" (Hosmer and Lemeshow, 2000).

In consideration of needing a larger statistical sample of students who did not return to engineering, the 2004 and 2005 cohorts were combined for this analysis. With 45 students who left engineering, a model may include 4 parameters. Therefore, no cross-validation of the model with a second sample was possible. The sample size is 735 with 690 students returning to Engineering for the second year of college and 45 students leaving Engineering. Of the 45 who left, 27 transferred to another college at Michigan and 18 did not register in the fall term of the 2nd year. It is assumed that they dropped out of college or transferred to another college.

Hypotheses

To validate the model for student retention, the following hypotheses were developed:

- The first year GPA a significant predictor for college retention
- The first year GPA a significant predictor of university retention

6.1.2 Results

Discussion of the H-L Goodness of Fit Statistic

In the methodology section, the literature indicated that the H-L goodness of fit statistic varies with software packages. A comparison was made of SPSS and Minitab and showed differences in the values of the H-L statistic for modeling of college retention as a function of the GPA (see Table 6-2). Because Minitab does not allow the modeling without a constant, the comparison was made with both the constant and the slope of GPA included in the logistic regression. In addition, a comparison was made by the coding of the dependent variable. The dependent variable is a binary 0-1 variable. Usually a "1" may be coded to indicate students who returned to engineering (indicating probability of retention). As an alternative method , a "1" may be coded to indicate student who left engineering (indicating the probability of leaving). Table 6-2 illustrates that the H-L statistic also varies depending on the coding of the dependent variable.

Table 6-2: H-L Goodness of Fit Statistics are Different between SPSS and Minitab and between the Retention and Attrition Models (n=735)

Coding Method of Dependent Variable	Software	H-L Statistic $\hat{C}$	p-value
1=Return; Predict College Retention	SPSS	8.280	.407
1=Return; Predict College Retention	Minitab	6.281	.616
1= Leave; Predict College Attrition	SPSS	5.882	.660
1=Leave; Predict College Attrition	Minitab	5.975	.650
Note; Logistic model includes both a constant and slope for GPA			

Overall Retention Statistics

The engineering college retention for the entire sample is 93.9% and the university retention is 97.6%. The empirical relationship of college retention to first year GPA is presented in Figure 6-2. As expected from the model, the lowest retention is for students with a first year GPA < 2.000.

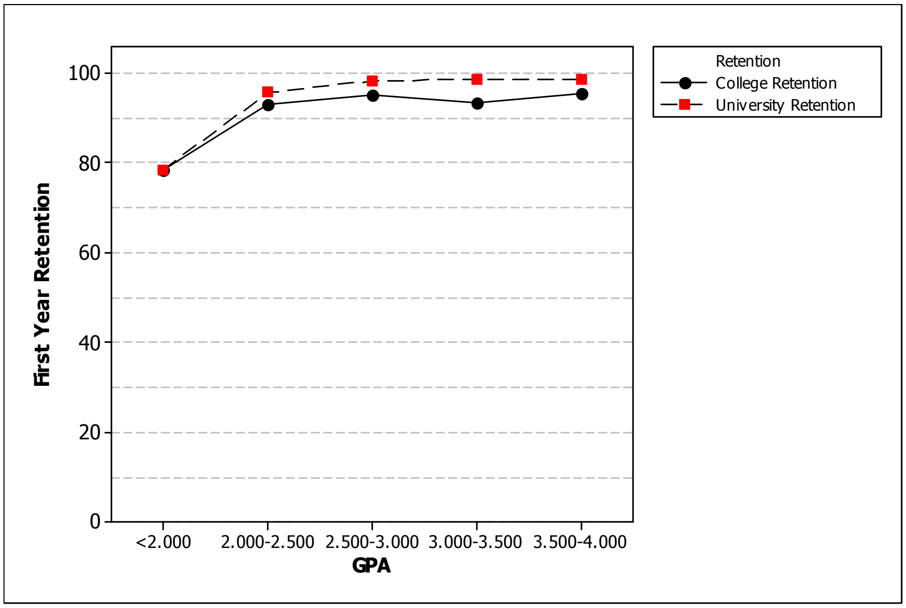


Figure 6-2: First Year Retention versus First Year GPA (n=735)

Modeling of Retention as a Function of GPA

Table 6-3 displays the logistic regression results for college retention and university retention with the GPA as a predictor.

Table 6-3: Logistic Regression Table for College Retention and University Retention Models (n=735)

Predictor	Coefficient	SE Coefficient	Wald's Test	P	Odds Ratio	95%Confidence Interval on Odds Ratio
College Retention						
First Year GPA	0.910	.053	293.8	.000	2.483	(2.238, 2.756)
Chi-Square Test = 17.62(p< .005) Unweighted Sum of Squares(Ŝ) Z-score= 3.166 (p=.001) Hosmer-Lemeshow Goodness of Fit Test (Ĉ) = 9.488 with d.f. =8 (p=.303)						
University Retention						
First Year GPA	1.312	.094	196.1	.000	3.713	(3.091,4.462)
Chi-Square Test = 106.55 (p<.005) Unweighted Sum of Squares (Ŝ) Z-score = 0.112 (p=.544) Hosmer-Lemeshow Goodness of Fit Test (Ĉ) = 8.010 with d.f. =8 (p=.433)						

The constant was not significant and was not included in the model. The three goodness of fit statistics discussed in the Methodology section are reported.

Disagreement in Goodness of Fit Statistics of Modeling of College Retention with the First Year GPA

For the college retention model, the H-L statistic and chi-square test indicate a good fit with a $p > .05$, while the unweighted sum of squares statistic indicates a poor fit. To better understand the logistic model, a graph of the observed and predicted college retention percent for each GPA in half-grade increments was generated. The expected college retention was calculated as the predicted retention at the mid-point of each interval (See Figure 6-3). The shape of the logistic curve does not have sufficient curvature to fit the expected retention for a GPA < 1.500. Figure 6-3 displays the inaccuracy in the fit between the actual data and predicted logistic curve.

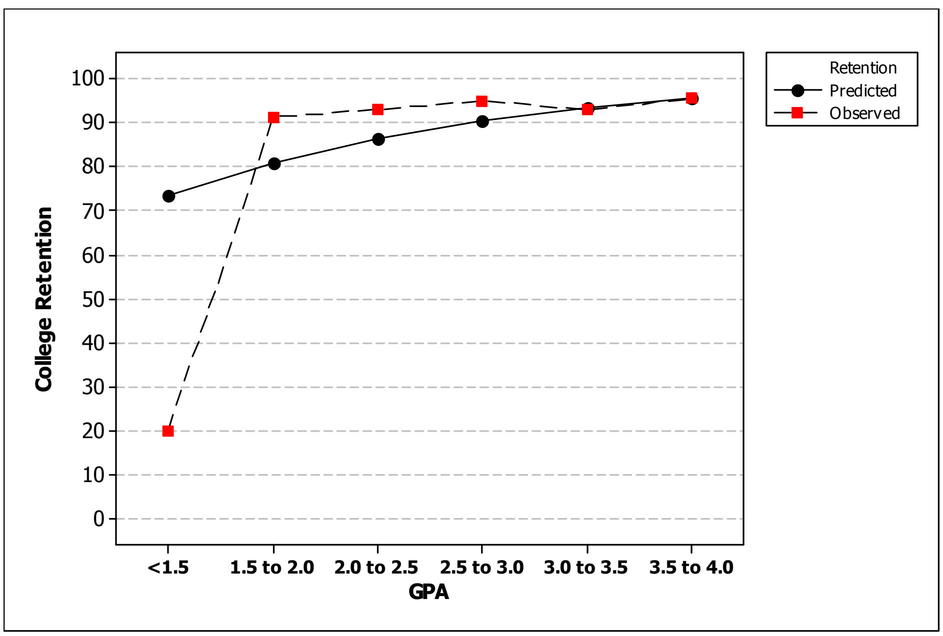


Figure 6-3: Weak Fit of Data with the Predicted College Retention Influenced by Low Retention of Students with GPA < 1.500 (n=735)

Only 5 data points were included in the retention statistics at the GPA< 1.500 point. A Minitab logistic regression diagnostic plot of "Delta Beta versus Leverage," confirmed that 4 of the 5 points exerted a high level of leverage to influence the regression coefficient. The logistic regression was re-run with without these five points, and the revised plot of predicted versus observed college retention is shown in Figure 6-4. The coefficient for the first year GPA was not significant (p=.245 with Wald's test), which left the model with only a significant constant term.

The logistic regression equation was :

$$\ln (P/(1-P) = 2.822 \tag{6.1}$$

Solving for P, the College Retention probability was:

P = .944 or 94.4 % for the range of first year GPA of 1.5 to 4.0 .

Using the goodness of fit statistics, the data fits a constant model. The Pearson chi-square statistic was 1.760 with 4 degrees of freedom (p=.778); the H-L statistic was 3.404 with 8 degrees of freedom(p=.094); and the unweighted sum of squares Z-score was .031 (p=.622). For the unweighted sum of squares, the same standard deviation was assumed as was used with the five points included. All three tests show a significance level greater than .05, indicating a good fit.

Modeling of University Retention of Engineering Students Shows that the GPA is Significant

In the modeling of university retention, a similar case of a poor fit of the data occurred at the low end of the distribution. Four of the five students (20%) with a GPA less than 1.500 left the university. Both the H-L statistics and $\hat{S}$ statistic indicated a good fit. Again, the SPSS logistic regression was re-run without the data with a GPA less than 1.500. For university retention, the GPA predicted the university retention. The difference from Table 6-1 was slight with the coefficient for GPA equal to 1.322 with no constant coefficient. The Pearson chi-square test value was 106.55 (p<.050); the H-L test value was 7.931 (p =.440); and the unweighted sums of squares $\hat{S}$ expressed as a Z-score was -1.07 (p=.160). The H-L test and the Ŝ indicate an adequate fit. Figure 6-5 shows the revised plot of the predicted University retention versus the observed retention.

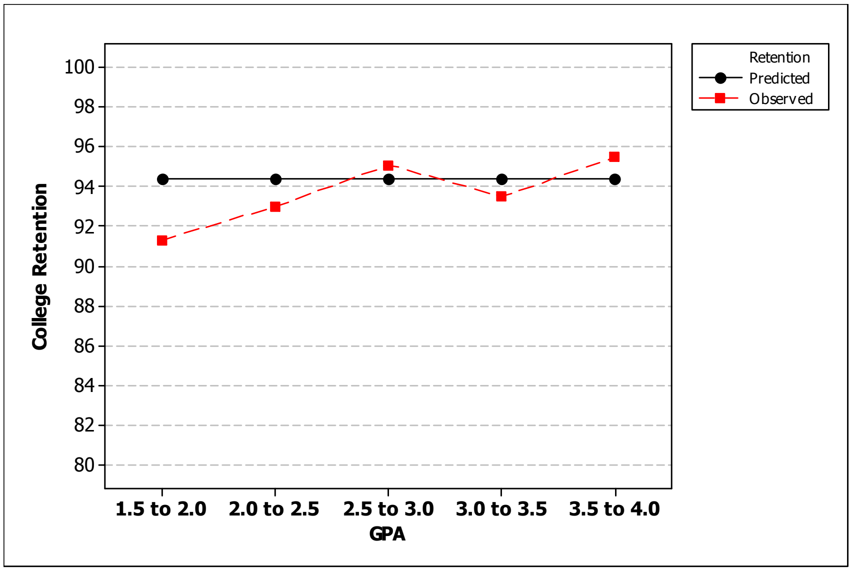


Figure 6-4 : Better Fit of Retention for GPA > 1.500 When a Constant Model of the Log of the Odds Ratio is Assumed (n=730). Note change in scale from Figure 6-3.

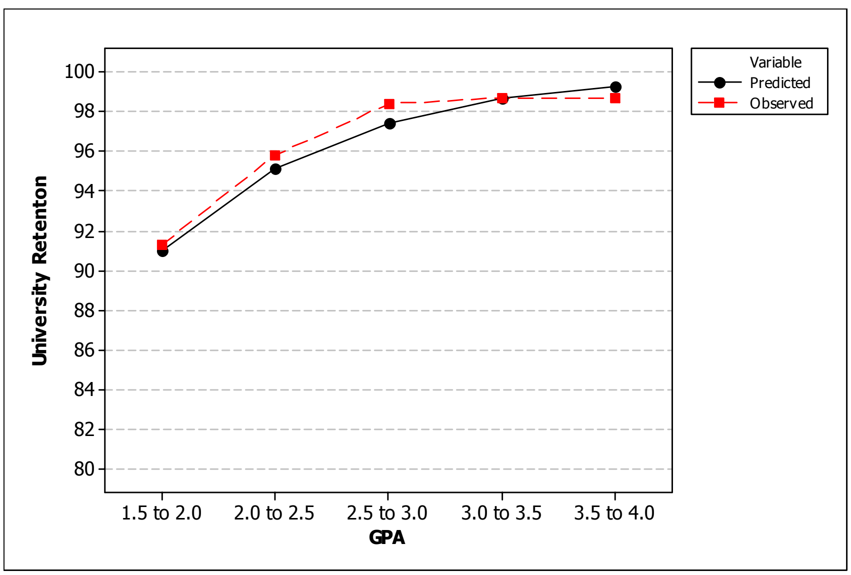


Figure 6-5: Revised Logistic Regression Model is Consistent With University Retention Data (n=730)

6.1.3 Discussion

The retention rates for engineering students were 93.9% for college retention (within the College of Engineering) and 97.6% for university retention.

The hypotheses were:

1. The first year GPA is a significant predictor for college retention
2. The first year GPA is a significant predictor for university retention

The GPA was not confirmed as a significant predictor of engineering (college) retention. It is possible that due to Michigan's support of students on probation that students with low GPAs perceive that they will be able to recover academically in their sophomore year.

The GPA was confirmed as a significant predictor of university retention.

6.2 Modeling Retention as a Function of the Pre-College Characteristics

Since the first year GPA was not a significant predictor of college (engineering) retention (section 6.1), a wider net of possible predictors was explored. In Chapter V, it was discussed that several of the factor scores were very significant predictors of the first year GPA. It is possible that instead of the first year GPA predicting retention, these same variables would predict retention.

6.2.1 Methodology

Missing Data Considerations Require Using Variables Instead of Factors

In considering this approach, there was a significant data management challenge. Of the 45 students whose data is present in the combined 2004 and 2005 cohorts database, only about half have all the factors present (no missing data). In addition, if the ACT- or SAT-based factors were used, missing data was present with the use of either admission test. To maximize the effectiveness of the analysis and minimize loss of data from students who left Engineering (due to missing data), this analysis used the original variables. The UM Math placement and UM Chemistry Placement scores were substituted for the ACT and SAT test scores since almost all students took the placement tests. The combined 2004 and 2005 cohort with an overall sample of 735 engineering students was used for this analysis.

Discriminant Analysis Combined with Logistic Regression

Both discriminant analysis and logistic regression were used. With the discriminant analysis, a stepwise algorithm available in SPSS 15.0 was utilized to determine the significant variables; then these variables were included in a logistic regression.

The discriminant analysis included two groups: those who returned to Engineering for the second year and those who left Engineering. The F to enter was set at p=.05 and the F to remove was set at a p=.10. The algorithm entered the variable that minimizes the sum of unexplained variation. The total sample size was 735.

6.2.2 Results for Modeling College Retention with Pre-College Characteristics

6.2.2.1 Significant Predictors for College Retention are: Self-Rating of Math Ability, High School Rank, Concern about Finances and Chance to Participate in a Study Abroad Program

From the discriminant analysis, the following variables were found to be significant discriminants for College retention.

- Self-Rating of mathematical ability
- High School Rank
- Concern about Finances
- Chance to Participate in a Study Abroad Program

71% of the 735 students were correctly classifies as stayers or leavers. 72% of the stayers were correctly classified and 58% of the leavers. With a binomial test, it was found that this classification was significantly better than a random occurrence (50/50).

From the logistic regression, the logistic model is :

$$\ln(P/(1-P)) = -6.020 + 0.820 * \text{Self-Rating of Math Ability} + 0.083 * \text{High School Rank} - 0.717 * \text{Concern about Finances} - 0.500 * \text{Chance to participate in a Study Abroad Program} \qquad 6.2$$

The typical range of values for each variable is shown in Table 6-4 with the logistic regression table displayed in Table 6-5. The significance of Wald's test for each coefficient was less than .05, indicating significance for all four coefficients.

Table 6-4 : Range of Values for Variables in Logistic Prediction

Variable	Coefficient	Scale Range	80% Range in data
Constant	-6.020	N/A	N/A
Self-Rating of Math Ability	0.820	1 to 5	3 (Average) to 5 (Top 10%)
High School Rank	0.083	Continuous	91 to 99%
Concern about Finances	-0.717	1 to 3 (None, minor, major)	1 (None) to 3(Major concern)
Chance to Participate in a Study Abroad Program	-0.500	1 to 4	1 (no chance) to 4 (high chance)

Table 6-5: College Retention Stepwise Logistic Regression Results for Engineering Students Using Pre-College Characteristics (n=694)

Variables in the Equation for College Retention

	B	S.E.	Wald	df	Sig.	Exp(B)	95.0% C.I.for EXP(B)	
							Lower	Upper
Math Ability	.820	.249	10.881	1	.001	2.272	1.395	3.699
H.S. Rank	.083	.031	7.313	1	.007	1.087	1.023	1.155
Concern about Finances	-.717	.267	7.197	1	.007	.488	.289	.824
Study Abroad	-.500	.189	7.001	1	.008	.606	.419	.878
Constant	-6.020	3.132	3.694	1	.055	.002		

For measures of goodness of fit, both the H-L goodness of fit statistic, $\hat{C}$, and the unweighted sum of squares expressed as a Z-score were computed. For the H-L goodness of fit statistic, the calculation was made using both SPSS and Minitab, and coding the state of a student returning to Michigan Engineering as either a “1” or a “0”. Table 6-6 displays the variation in $\hat{C}$. The unweighted sum of squares did not vary under these conditions and its Z-score was calculated as .029 (p=.386).

Table 6-6: Comparison of the H-L Goodness of Fit Statistic

Description of Logistic Regression	**Software**	**H-L test C**	**p- level**
Student Returns =1 (Retention) 651 Return, 43 Leave	SPSS	15.998	.042
Student Leaves = 1 (Attrition) 43 Leave, 651 Return	SPSS	12.892	.116
Student Returns = 1 (Retention) 651 Return, 43 Leave	Minitab	10.754	.216
Student Leaves =1 (Attrition) 43 Leave, 651 Return	Minitab	7.657	.468

Sample size information: 651 students return and 43 students leave.

The SPSS output using a “1” for coding students who returned was the only case of a significant goodness of fit of the H-L statistic. Because the other three H-L statistics and the unweighted sum of squares indicated a good fit, it was assumed that the fit of the data to the model was reasonable.

The self-rating of math ability is more significant than the U-M Math Placement test, indicating that the affective perception of math ability was more significant than actual math knowledge as measured by the placement test.

The significance of “chance to participate in a study abroad program” was an interesting and unexpected predictor. This was an important issue since the current thinking in the engineering community is that students need more exposure to global engineering. The model suggests that students with a high interest in a study abroad program at the beginning of the freshman year have a lower first year retention than students who are not interested in a study abroad program.

The chance to participate in a study abroad program is a CIRP survey question with four possible responses to the question: “What is your best guess as to the chances that you will participate in a study abroad program.” The four responses are

- 1= No chance
- 2= Very little chance
- 3=Some chance
- 4= Very good chance

It was found that there was an inverse relationship between the self-rating of math ability and chance to participate in a study abroad program. Further analysis showed that the students who replied “no chance” had the highest self-rating of math ability, the highest ACT Math Score and highest high school GPA. The variable entered the regression because there was a significant difference in the retention among the four levels of the study abroad variable (99% for “no chance” down to 90% for “very good chance”).

Female students were more interested in a study abroad program than male students . Adding the two top categories (some chance and very good chance) together, 74% of the female students thought that there was at least some chance of participating in a study abroad program. Only 50% of male students responded in the same way (p=.000 for a difference in percents with a binomial test).

6,2.2.2 Sensitivity Analysis of College Retention using Model

It is important to understand why Michigan has a high retention rate and how much it could vary. By using the logistic regression equation, a sensitivity analysis on the range of the each variable and its effect on predicted retention was calculated. The logistic regression was viewed as a regression of the four variables against the retention rate for the ith student and is given by:

$$\ln (P/(1-P)) = -6.020 + 0.820 \text{ (High School Rank)} + 0.083 \text{ (Math Ability)}$$
$$-0.717\text{(Concern about Finances)} \ -0.500\text{(Study Abroad)} \qquad 6.3$$

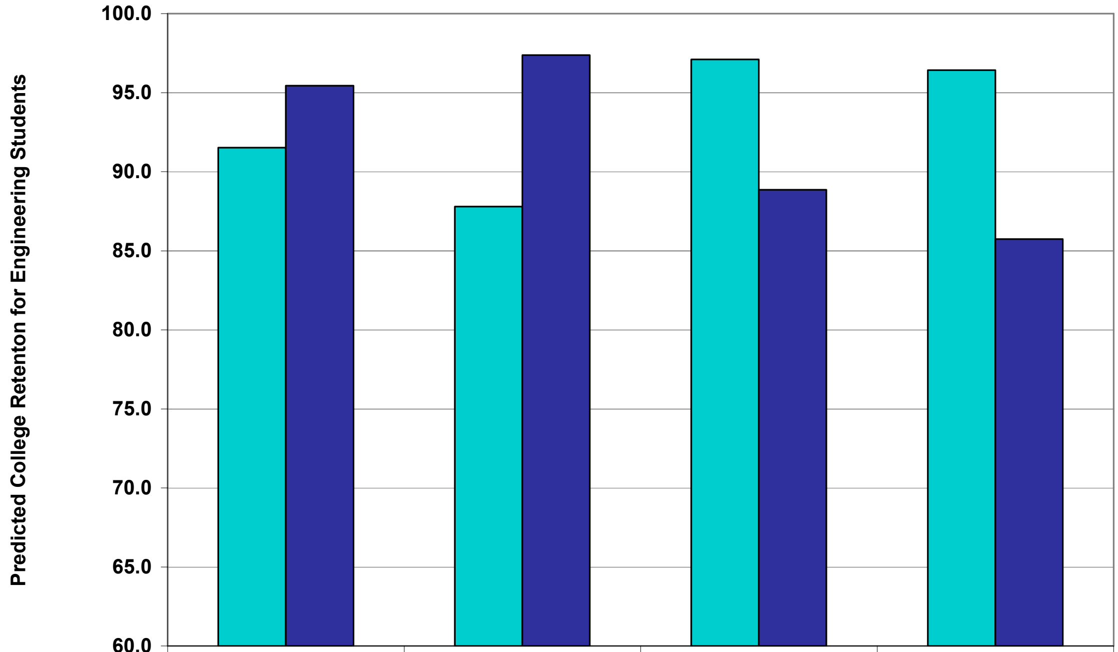
where the odds ratio is (P/ 1-P) and P was the predicted retention for the ith student. Using the estimates of the coefficients derived from the logistic model, a predicted value of ln (p//1-p) was calculated. Back-solving equation 6.3, the predicted college retention probability for engineering students was:

$$P = 1/(1+ \text{EXP} - \ (-6.020 + 0.820 \text{ (High School Rank)} + 0.083 \text{ (Math Ability)}$$
$$-0.717\text{(Concern about Finances)} -0.500\text{(Study Abroad)})) \qquad 6.4$$

Review of the four predictors established a low value, median value and high value for each variable. The low value was approximately the 10 to 20 percentile and the high value was approximately the 80 to 90 percentile (See Table 6-7). Using equation 6-4, the sensitivity analysis on retention (p) included varying each variable from the low and high values, keeping the other variables at the median value. The range of predicted retention is presented in Figure 6-6.

Table 6-7: Low, Median and High Values of the Predictors For Engineering (n=694)

Variable	**Low Value**	**Median Value**	**High Value**
High School Rank	91%	96%	99%
Self-Rating of Math Ability	3 (Average)	4(Above-Average)	5(Top 10%)
Concern of Finances	1(None)	2(Some)	3(Major)
Chance to study abroad	1 (No chance)	2 (Very little chance)	4 (High Chance)



	HS Rank	Math Ability	Fin Concern	Study Abroad
low value	91.5	87.8	97.1	96.4
high value	95.4	97.4	88.9	85.7

Figure 6-6: Predicted First Year College Retention of Engineering Students Shows a Potential Variation in College Retention of 88% to 97% (n=694)

Significantly, the sensitivity analysis showed that within the current range of the four variables, the first year retention had possibilities of dropping below 90%. Interestingly, the study abroad variable showed the most variation. The low value for retention for students with a major concern about finances was consistent with the data. Of the 8% of the students in the sample who had a major concern about finances (in the CIRP survey), 86.7% were retained in the College.

6.2.3 Results for Modeling University Retention with Pre-College Characteristics

6.2.3.1 Significant Variables for University Retention are High School Rank and Concern about Finances

The university retention for the engineering students is the percent of students who returned to Michigan, even if they left Engineering. 717 out of 735 students returned to the University. Again, a discriminant analysis was run and the leading predictors were high school rank, the U-M math placement score and the CIRP variable, concern about finances. 84% of the students were correctly classified; 85% of the stayers were correctly classified and 63% of the leavers. Again, the results of the discriminant analysis were significantly better than random chance using a binomial test for proportions (p=.000).

Next, a logistic regression was run with these variables and the regression results are shown in Table 6-8. Due to the small sample size of 18 students who left Michigan and using the 10 samples/ parameter rule, only the first two variables from the stepwise regression were allowed in the final model. These two predictors of university retention were high school rank and concern about finances. The H-L goodness of fit statistic, $\hat{C}$, was 8.775 (p=.187) and the unweighted sums of squares statistic, $\hat{S}$,as a Z-score was .121 (p=.548). Both statistics indicated a good fit of the data to this model.

Table 6-8: Logistic Regression Table for University Retention of Engineering Students (n=705)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1	High School Rank	.177	.038	21.717	1	.000	1.193
	Concern about Finances	-1.386	.449	9.526	1	.002	.250
	Constant	-10.187	3.498	8.483	1	.004	.000

In section 6.1, it was found that the first year GPA was a significant predictor of university retention**.** Using the pre-college variables, high school rank and concern about finances was also significant. The comparison of the two models is made in Table 6-9.

Table 6-9 Comparison of Models for University Retention

Model	H-L Statistic Goodness of Fit test (p-level) (more is better) with SPSS	H-L Statistic Goodness of Fit test (p-level) (more is better) with Minitab	Unweighted Sum of Squares $\hat{S}$ (p-level)	Wald's test for coefficient (p-level)
First Year GPA, No constant from Section 6.1.2 (n=730)	0.440	Not available With Minitab	0.160	p=.000
High School Rank Concern about finances (n=705)	0.187	0.291	0.548	High school rank p=.000 Concern about Finances P=.002

The two models are comparable. The following metrics were used in the comparison of the two models. Both the H-L goodness of fit test from SPSS and Minitab were calculated along with the $\hat{S}$ as measures of goodness of fit. In addition, the Wald's test on the significance of the coefficient in the model was considered. For the model with the GPA, the H-L statistic indicates a higher p-value and it is assumed that this is indicative of a better fit. However, the $\hat{S}$ indicates a better fit for the High School Rank model. The Wald test is highly significant in both cases. In addition, the Model Chi-Square test with the SPSS software tests the significance of the model with the added variables as a difference in maximum likelihoods. For both models, the p-level for this statistic had a p-level of .000.

The conclusion is that both data fit both models. The model (Figure 6-1) identified the importance of the GPA through the literature review. Some literature supports the significance of the high school rank as a predictor.(Besterfield-Sacre et al. , 1997; Scalise et al., 2000) As a confirmation of choosing the best model, the three variables were entered into a stepwise logistic regression and the high school rank was selected in step 1 with concern about finances selected in step 2 of the regression. Based on this, it was decided that the second model with the high school rank and concern about finances was the preferred model...

6.2.3.2 Sensitivity Analysis of University Retention using Model

Similar to the sensitivity analysis for college retention, Figure 6-7 displays the sensitivity analysis for university retention.

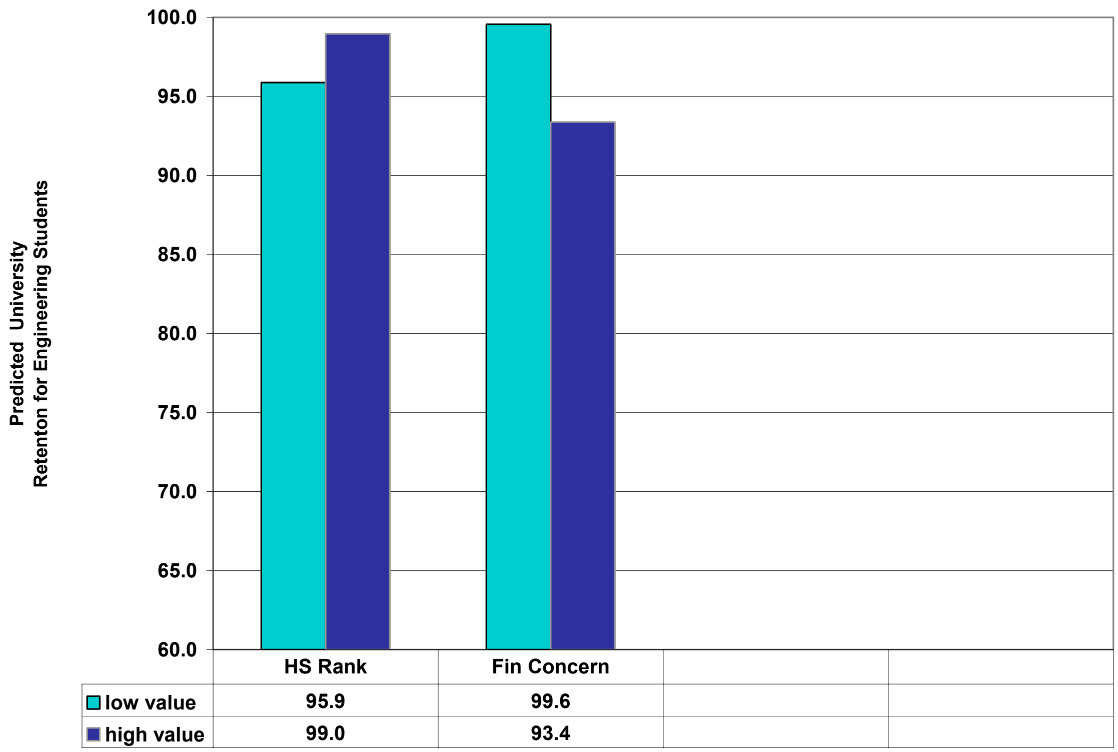


Figure 6-7: Predicted First Year University Retention of Engineering Students Shows a Potential Variation in University Retention of 93% to 100% (n=705)

6.2.4 Gender and Ethnicity Effects

When gender and ethnicity were considered in the stepwise logistic regression model, they were not significant for either college or university retention. This indicates that the four predictors for college retention explain any significant difference between genders and under-represented and non-under-represented groups. Similarly, the two predictors for university retention explain any significant differences that may exist for gender or ethnicity. With these variables in the model, neither gender or ethnicity are significant.

6.2.5 Discussion

Combining the 2004 and 2005 cohorts, the college retention for engineering students was 93.9% and the university retention was 97.6%. In this section, the pre-college characteristics were considered as predictors of college and university retention using stepwise logistic regression. Initially, with the limitation of 10 observations for each parameter, it was thought that a model for college retention would be limited. However, the findings showed that all identified significant pre-college variables were entered. Because of the missing data among the factor scores, the individual variables were used with some guidelines to reduce the missing data.

In the case of the modeling of college retention of engineering students the four variables that were most significant were:

- Self-rating of math ability,
- High school rank,
- Concern about finances and
- Chance to participate in a study abroad program.

The sensitivity analysis showed that within the range of these significant variables, the college retention could range from 86% to 97%.

In the case of the modeling of university retention, the first two variables in the stepwise logistic regression were:

- High school rank and
- Concern about finances.

The sensitivity analysis showed that the university retention could vary from 93% to 100% within the range of current levels of high school rank and concern about financing a college education.

The significant predictors are consistent with the data of the students who left engineering and Michigan. Eighteen engineering students left Michigan. Of these, 8 (44%) had a high school rank less than or equal to the 90 percentile. Six (33%) had a major concern about financing a college education, and 7 more (39%) had some concern about financing a college education. Five were underrepresented minorities, all with a high school rank ≤ 90. Six were female students (33%), three of which had a high school rank ≤ 90 and 3 had a major concern about finances. Nine (50%) were recommended for placement into the pre-calculus course, indicating low quantitative skills (for engineering). Six students earned a first year GPA of 3.00 or better, so the decision to leave Michigan was probably not based on their academic performance. 12 out of the 18 (67%) indicated a good chance of changing careers.

In the literature review in Chapter II, substantial evidence was presented that the college GPA was a significant predictor in logistic regressions for the engineering college retention. Only the Seymour and Hewitt (1997) showed that academic performance was not a predictor of retention. The difference may be because of the highly selectiveness of Michigan. 78% of the students considered Michigan as their first choice. Leaving may have more perceived risk than staying, even with a GPA < 3.000. For engineering college GPA, the first three significant variables were self-rating of math ability, high school rank and concern about finances. In Besterfield-Sacre et al (1997) study, a logistic regression on retention of freshmen showed that high school rank and "enjoyment of math/science courses," and "confidence in basic engineering knowledge" were significant predictors. "Enjoyment of math/science courses" and "confidence in basic engineering knowledge" can be considered similar to self-rating of math ability. (If a study has a high self-rating of math ability, he/she would tend to enjoy math courses.) In an eight-semester retention study, French et al. (2005) conducted a logistic regression for engineering retention, and found that both the GPA and high school Rank were significant along with the SAT Math score and a motivation score. Therefore, there is support in the literature for the revised retention using pre-college characteristics. The high school rank is a measure of the ranking of the student's grades; In order to earn high grades, a high school student intrinsically must be motivated, be well-organized and competitive for grades. Because of the competitiveness of the freshman engineering program at Michigan, it can be hypothesized that students who have a high rank will do well and be retained. Students who are less competitive or less organized may be overly-challenged and decide to leave engineering.

In summary, the hypothesized model in Figure 6-1 was not validated with respect to the first year GPA influencing the college retention of engineering students after the first year. The first year GPA was not a significant predictor of the college retention. Perhaps a longer time frame is needed to see a relationship between GPA and retention. Students exist in the sample with a GPA < 2.000 who decided to return to engineering for their second year of college, even though they are on academic probation (assumed). It can be inferred that with the support systems in place at Michigan, students believe they will improve their GPA. For university retention, the high school rank was a better predictor than the first year GPA.

When these predictors are taken into account, there was no significant difference in retention by gender or ethnicity. This was consistent with the research of Leuwerke et al. (2004), who found no difference in the "differential attrition rates for female or minority students" in a freshman retention single institution study. In addition, in a logistic regression model for first term engineering probation, similar retention percentages were obtained for male and female students (Scalise et al., 2000) . Adelman found that for students who were well-prepared for engineering, "the degree completion gap in engineering between men and women is negligible." (Adelman, 1998, p. 67)

6.3 Validating the Model Using the Initial Commitment to Engineering and the University of Michigan

In validating this model, it is reasonable to ask whether the initial commitment to an engineering major, to an Engineering career or to Michigan affect a student's retention decision. A statistical analyses found no statistically significant difference between students who indicated a probable major or career in Engineering and students who indicated a probable major or career in a non-Engineering field. There was no significant difference between students who considered the University of Michigan their first choice college and students who considered another engineering college their first choice. (See Table 6-10.) In response to the survey question of college choice, 78% of the students indicated that Michigan was their first choice for college. This compares to 71% of all public universities in the 2005 CIRP survey (Pryor et al, 2005).

Table 6-10: Retention Hypotheses and Results

Null Hypothesis	CIRP Variable	Statistic (2-sided test)	College Retention Significant at p=.050	University Retention Significant at p=.050
Retention percentages are equal for Engineering major and Non-Engineering major (n= 698, 32)	Probable major	2x2 Chi-square	No	No
Retention percentages are equal for Engineering career and Non-Engineering career (n=537, 176)	Probable career	2x2 Chi-square	No	No
Retention Percentages are equal for U-M as the first choice college and U-M as the 2nd choice or more college (n=564, 165)	Choice	2x2 Chi-square	No	No

6.4 Does Engineering 110 and Advising Contribute to Higher Retention?

In Chapter V, Engineering 110 and frequency of visits to the Engineering Advising Center (EAC) were considered for their contributions to the improvement in the first year GPA of engineering students. In this section, the discussion will continue to explore the effectiveness of improving the college retention and university retention of engineering students with either enrollment in Engineering 110 or a higher frequency of advising visits to EAC.

6.4.1 Methodology

Two variables were considered: enrollment in Engineering 110 and frequency of advising visits to EAC. Engineering 110 is an elective 2-credit survey course on engineering careers. All engineering students visit EAC for advising on courses, academic and general counseling. A low frequency of advising sessions was defined as four visits or less. A high frequency was defined as five or more visits. Considering the extent of counseling that the advisors provide, a more comprehensive measure of the content of the advising would be desired. An analysis by frequency of advising visits was viewed as an overall objective metric of the amount of advising.

For both retentions, two null hypotheses were developed:

Hypothesis 1: There is no difference in retention rates between students who visited EAC at a high frequency and students who visited who visited EAC at a low frequency.

Hypothesis 2: There is no difference in retention rates between students who enrolled in Engineering 110 and students who did not enroll in Engineering 110.

Data analysis included descriptive statistics and graphs and chi-square tests. The chi-square tests were conducted on 2x2 contingency tables of retention (yes, no) versus both enrollment in Engineering 110 and a low or high frequency of advising visits. Retention can be considered as a proportion and the chi-square tests for significant differences in proportions. The sample sizes for enrollment in Engineering 110 and advising frequency level are shown in Table 6-11. Based on the sample sizes, the type II error (of concluding there is a difference when no difference exists) was calculated for any significance differences in retentions. It was assumed that not being enrolled in Engineering 110 and Low Frequency were the standard conditions. With the sample size > 500 for each of these conditions, this proportion is considered standard and "known". Enrollment in Engineering 110 and a High Frequency of advising are considered the "experimental" condition. The Minitab program for power curves was used to calculate the power and type II error based on the test for proportions.

Table 6-11 Sample Sizes for Enrollment in Engineering 110 and Advising Frequency

			Advising Frequency		
			Low Frequency	High Frequency	Total
Engin 110	Engineering 110-Not Enrolled	Count	391	116	507
		% of Total	53.2%	15.8%	69.0%
	Engineering 110-Enrolled	Count	174	54	228
		% of Total	23.7%	7.3%	31.0%
Total		Count	565	170	735
		% of Total	76.9%	23.1%	100.0%

6.4.2 Results

The results can be summarized in three categories and they are listed in this section.

1) No Significant Difference in Retention Due to Advising Frequency Level

All students visited the EAC for course scheduling advice and initial placement into courses. 23% of the students visited the EAC at a high frequency. The Pearson chi-square test did not show a statistically significant difference in retention between the students with a higher level of advising compared to the students with a lower level of advising. The power of this test was only .05, due to the small difference (less than 1%) of detection in the proportions.

Using the variables in the database, the following profile of students who visit EAC for advice at the higher rate (compared to those who visit EAC at the lower rate) emerged from the data. Their preparation in math and science as indicated by the admission and placement tests is weaker; their average first term GPA is significantly less; they carry an average of 2 credits less in the first semester; their overall high school academic achievement as measured by the high school GPA and rank is not significantly different. In addition, they have a significantly higher concern about financing college and are more likely to change their major. 40% of all female freshmen visit EAC at the higher rate; this is statistically significant. The percent of under-represented minority students who visit EAC at a high rate is not significant compared to their percentage of the student population. In summary, students who visit EAC at the higher frequency have significantly lower average academic performance, are more concerned about their finances and less sure about an engineering major; all these are factors related to engineering retention.

2) Significant Difference in College Retention Due to Engineering 110 Enrollment

The Pearson chi-square test showed a significant difference in college retention rates between students who enrolled in Engineering 110 and students who did not enroll in Engineering 110 at p=.021. (See Figure 6-8) The power of the chi-square test is 88% (type II error is 12%) . The college retention for students who enrolled in Engineering 110 was 96.9% compared to 92.5% for students who did not enroll in Engineering 110, yielding an average improvement of 4.4%. The difference was not significant for university retention. The power of the test was .73 (type II error of .27).

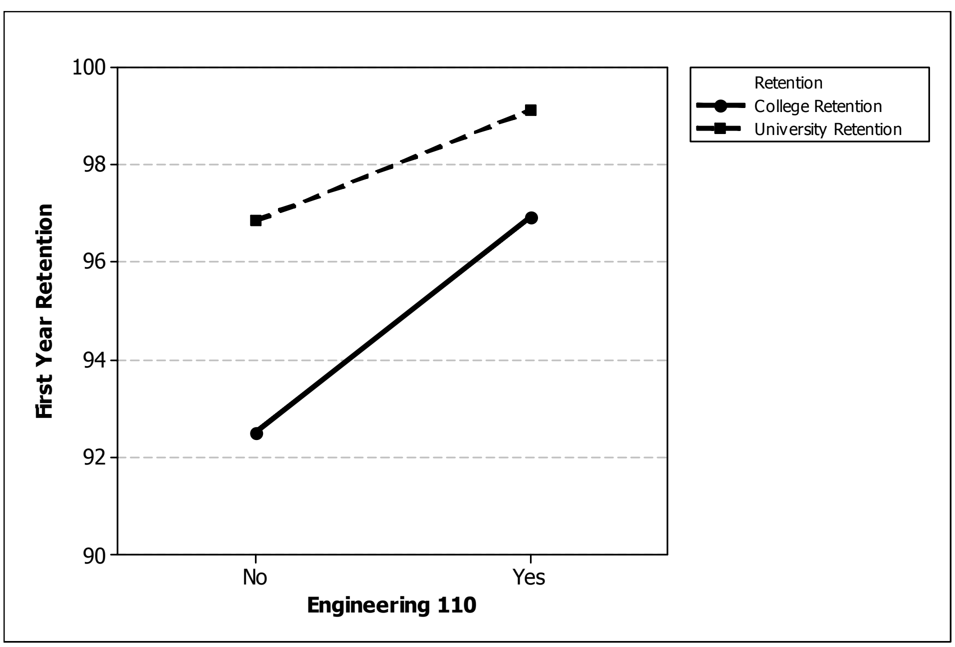


Figure 6-8: Enrollment in Engineering 110 Shows Higher Retention Rates (See Table 6-8 for sample sizes)

3) Selection of Students for Engineering 110

Currently, Engineering 110 is an elective course, with approximately one-third of the freshman class enrolling in Engineering 110. It is possible that certain subgroups of the freshman class will benefit from this course. For example, students with a low college GPA may be motivated by the course to continue in engineering studies. To understand the effectiveness of Engineering 110 and possible recruitment strategies into Engineering 110, variables that had been considered in the previous analyses were explored for a predictive relationship with college retention. In particular, the relationship between enrollment in Engineering 110 and advising level, the relationship between enrollment in Engineering 110 and first year GPA, the relationship between enrollment in Engineering 110 and high school rank, and the relationship between enrollment in Engineering 110 and concern about finances were explored. This analysis suggests that there are some meaningful treads present that could aid in a student retention strategy. However, confirmatory research studies are recommended in the future.

Analysis Shows Engineering 110 AND a High Advising Level Helps Students

Because of the significance in Engineering 110 for college retention, an exploratory research effort was made to review college retention. As the analysis proceeded, an interesting trend developed in terms of both student success and retention for students who enrolled in Engineering 110 and visited the EAC at a high frequency. Figure 6-9 displays the interaction plot between advising frequency and enrollment in Engineering for college retention.

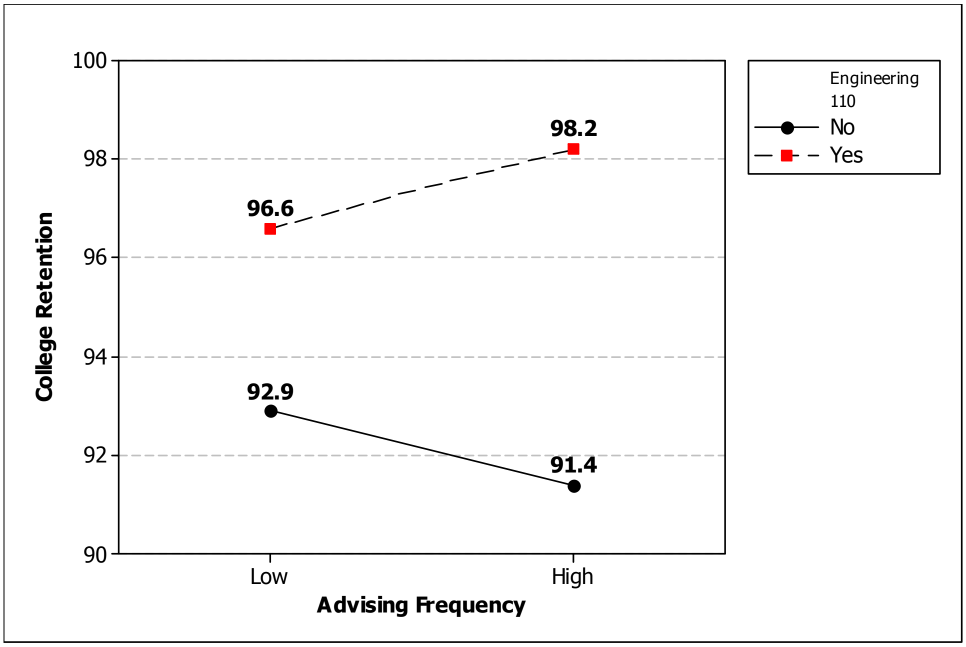


Figure 6-9: Enrollment in Engineering 110 Complements Advising Frequency to Increase College Retention Rate (See Table 6-8 for sample sizes)

As illustrated, the students who sought the higher level of advising and enrolled in Engineering 110 had the highest level of retention in the College of Engineering. Taking into account that students who have the higher level of advising are generally higher at risk of leaving engineering, this is a significant piece of information.

Engineering 110 Motivates Students with a GPA of 3.000 to 3.500 to Stay in Engineering.

Although the logistic regression in Section 6.1 did not show a significant relationship between GPA and college retention, I explored this relationship including viewing retention with respect to enrollment in Engineering 110. See Figure 6-10. A Chi-square test showed a significant difference in retention for enrollment in Engineering 110 for the group of students who earned a 3.0 to 3.5 GPA. Note that for the group with a GPA <2.0, the total sample size was 28 and the difference in retention rates was not statistically significant.

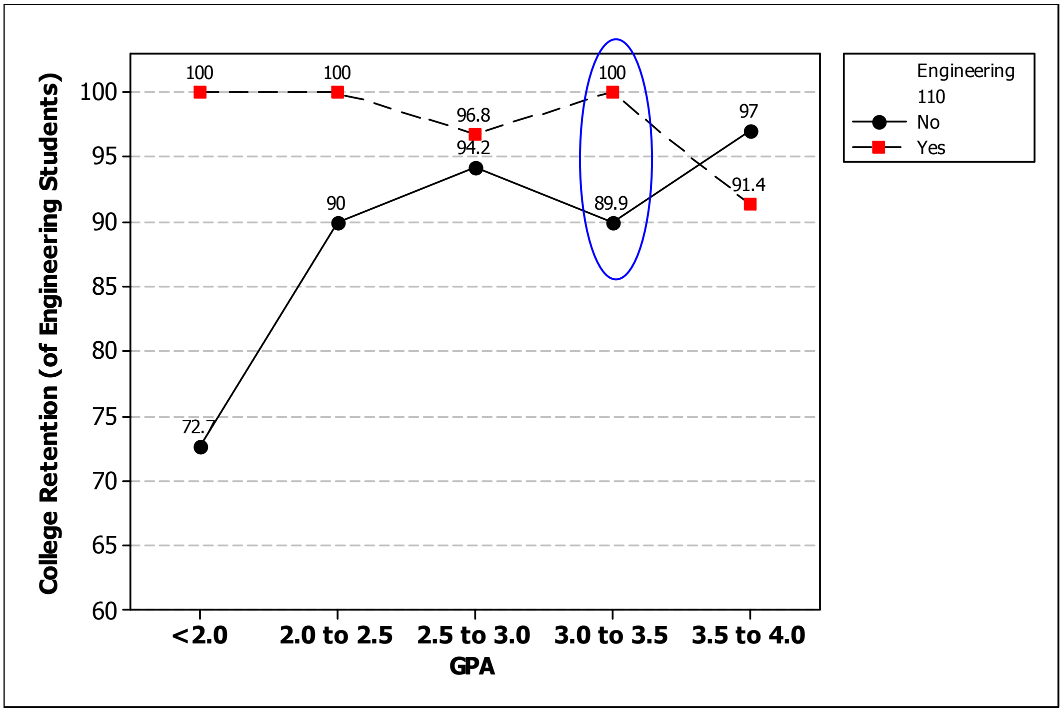


Figure 6-10: College Retention Improves with Enrollment in Engineering 110: Engineering 110 is Significant for Students with a GPA between 3.0 and 3.5 (combined sample size = 28 for GPA < 2.0, 71 for GPA=2.0 to 2.5, 182 of GPA = 2.5 to 3.0, 230 for GPA= 3.0 to 3.5, and 224 for GPA= 3.5 to 4.0)

Engineering 110 Motivates Students with a High School Rank < 96% to Stay in Engineering

Because of the significance of high school rank as a predictor of college retention, the effect of Engineering 110 in terms of the high school rank was considered. The data in the database was divided into three nearly equal groups by high school rank. The three groups were: students with a high school rank of 99% were placed in the first group; students with a high school rank of 97 to 98% were placed in the second group and students with a high school rank of 96 or less were placed in the third group. (Approximately 90% of the students in this survey (who reported high school rank) had a high school rank greater than 91%.) Figure 6-11 displays the college retention for each high school rank group. For the group with a high school rank of 96% or less, the students who enrolled in Engineering 110 showed a significantly higher college retention than students who did not(chi-square test, p =.000, type II error < .05).

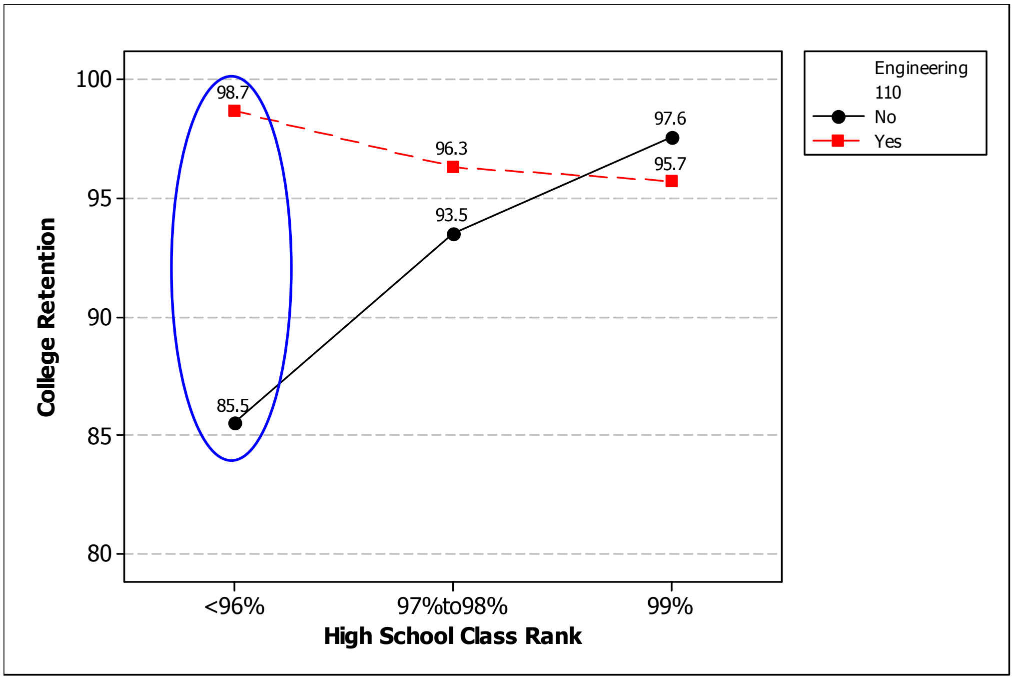


Figure 6-11: Significant Difference in College Retention Between Students With a High School Rank < 96% and Enrolled in Engineering 110 versus Not Enrolled in Engineering 110 (combined sample size = 234 for rank<96%,244 for rank of 97 to 98%, and 232 for rank of 99%.)

Relationship between Enrollment in Engineering 110 and Concern about Finances

Interestingly, students who initially indicated a major concern about finances and enrolled in Engineering 110 had a significantly higher retention rate (96.7%) than students who did not enroll in Engineering 110 (91.1%) using a chi-square test (p=.047).

University Retention

Only 0.9% of the students who took Engineering 110 dropped out compared to 3.2% for students who did not take Engineering 110. This difference was not statistically significant using the chi-square test (p=.064).

6.4.3 Discussion

Two null hypotheses were tested:

Hypothesis 1: There is no difference in retention rates between students who visited EAC at a high frequency compared to students who visited who visited EAC at a low frequency.

There was not enough evidence to reject this hypothesis. As was presented in the results section, students who visit the EAC at a high frequency on the average have more issues with achieving at a high academic level, placement into courses, concerns about an engineering major and financing a college education. The fact that there was no significant difference is perhaps indicative of the success of the EAC in retaining students in engineering with the challenges of the freshman year. Of the students who visited the EAC at a high frequency, many with academic problems, a very high percent, 94%, return for the second year. This suggests that of the students serviced by EAC with a high frequency of visits, almost all of them valued this support and choose to return to Engineering for the second year of college.

Hypothesis 2*:* There is no difference in retention rates between students who enrolled in Engineering 110 compared to students who did not enroll in Engineering 110.

This hypothesis was rejected for college retention. The chi-square tests showed a significant difference for college retention for students enrolled in Engineering 110 compared to students not enrolled in Engineering 110. No significant difference was evident for university retention.

Evidence was presented that the enrollment in Engineering 110 combined with a high frequency of advising contributed to a higher retention rate. The group that showed a significant difference in enrollment in Engineering 110 was students with a GPA between 3.0 and 3.5. These students would be performing well with respect to grades; and if they had concerns about engineering major or career, the Engineering 110 could reinforce the excitement related to an engineering career. Students in the lowest third of the data by high school rank appear to benefit from enrollment in Engineering 110. Finally, of the students who indicated an initial concern about finances, students who enrolled in

Engineering 110 had a significantly higher retention rate than the students who did not enroll in Engineering 110. Although the relationship was not statistically significant, enrollment in Engineering 110 seems to influence university retention. A student takes Engineering 110 and decides to transfer to another college at Michigan. The data supports that the course influences the student not to transfer to another university. The dropout rate from Michigan of engineering students who enrolled in Engineering 110 was less than 1%.

The freshman year is a year of exploration; it is not surprising that some students transfer out of Engineering. Of the 45 students who left engineering at the end of the freshman year, most were not enrolled in Engineering 110. Although the retention rate is very high (94%), the data suggests that some of these students would have been retained in engineering if they had enrolled in Engineering 110.

In summary, both the advising services of EAC and enrollment in the Engineering 110 show success as intervention strategies for student retention. Evidence supports that the retention could be higher with a higher enrollment in Engineering 110. Conversely, without an Engineering 110 course, the freshman retention would have been lower.

6.5 Summary and Recommendations

The modeling of freshman engineering retention required an understanding of both college and university retention. Inherent in this modeling was the understanding that the freshman year must be thought as a year of transition from high school to college. A high university retention rate guarantees a low drop-out rate from college (any degree) and adds value to society. In the concept of retention and loss to society, for every drop-out, there is a loss to society. The student, who drops out, in most cases, will work at an entry-level job instead of enjoying a good career. Once a student drops out, there is no formal educational support system to help a student.

On the other hand, most important to a College of Engineering is the college retention rate. A high college retention rate guarantees a stable student population and minimizes the need to recruit engineering transfer students. The college retention rate can be viewed as a metric for the partnership between the college and the students. For a college of engineering that presents an excellent program, excellent support systems and recruits students who are both academically capable and interested in an engineering career, the engineering freshmen will see value in the program and decide to return for the second year.

In the case of Michigan, both the college retention and university retention are very high, 93.9% and 97.6% respectively. Because there is not a national database on college of engineering retention rates, it is difficult to compare this retention rates to other engineering colleges (Veenstra and Herrin, 2006b). Compared to available first-year university retention rates, these retention rates are very high. With modeling, we can understand Michigan's success. This study looked only at pre-college characteristics and the first year GPA to develop a model of first year retention.

College Retention of Engineering Students

The first year GPA was not validated as a strong predictor of college retention for engineering students. For college retention, self-rating of math ability and high school rank were the most significant predictors. The self-rating of math ability was a better predictor than the U-M math placement test score; this indicates that the student's initial perception of their math ability was more important than actual math ability. The importance of self-rating of math ability is consistent with the Astin and Astin multi-institutional study, which found that the same CIRP variable, high self-rating of math ability, was important for engineering retention (Astin, 1993). Besterfield-Sacre, et al. (1997) found a low level of "confidence in basic engineering skills" to be a strong predictor of engineering attrition. This variable is a component of the Pittsburgh Freshman Engineering Attitudes Survey © (PFEAS) and was similar to the self-rating of math ability on the CIRP survey. Research supported the high school rank as a predictor of freshman engineering retention. In the same study, Besterfield-Sacre, et al. (1997) found high school rank to be a significant predictor of retention. For a 4-year retention, French, et al. (2005) found that both college GPA and high school rank were significant predictors of engineering retention. For a freshman retention study involving non-engineering students, Allen (1999) found both high school rank and first year GPA to be significant predictors of retention.

In addition, two other variables were important predictors among the pre-college characteristics in the initial model. They were: initial concern about financing a college education and the chance that a student will participate in a study abroad program. With the high cost of college, it is well recognized that concern about finances is a negative contributor to college retention. (Allen, 1999; Tinto, 1993) In my literature search, very few engineering education studies showed financial concern to be a significant predictor of freshman retention. What was a surprise was the significance of interest in a study abroad program; and more interest predicted a lower retention. In the engineering community, exposure to a global engineering experience as an undergraduate engineer is now considered important in the current economic environment. More research is recommended about this predictor.

These variables have the potential of identifying students who need more support and providing organizational indicators for predicting retention.

University Retention of Engineering Students

The analysis of university retention for engineering students supported two models of retention; one included the first year GPA consistent with the model; the second include the high school rank and the CIRP variable, concern about finances, as predictors of university retention.

Conclusions

The following conclusions were reached on retention for the Engineering sector:

- The sensitivity analysis showed that the expected college retention could be as low as 86% within the range of the predictors. To maintain a high retention rate, the College of Engineering must recruit students with a high self-rating of math ability, a very high high-school rank, and be aware that some students transfer out because they are interested in a study abroad experience (or a characteristic highly correlated with this variable.) Concern about financing college was a significant predictor and needs further research.

- No statistically significant difference in retention between female and male students was evident. Since there was no significant difference in the average high school rank by gender, this is consistent with the model for retention.
- No statistically significant difference in retention between under-represented minority students and non-under-represented minority students was evident, once the retention was adjusted for the significant predictors. This was consistent with Allen's study, which compared minorities and nonminorities. He stated " for both minorities and nonminorities, pre-college academic ability (i.e. high school rank) was found to play a significant role on their cumulative grade-point average in college and on persistence behavior" (Allen, 1999).

Engineering Career Development and Engineering 110

Initially, when I considered intervention programs to support freshmen engineers, I considered only tutoring, mentoring and advising programs. As this research unfolded, I also considered Engineering 110, the survey course on engineering careers, as an intervention program for student retention. It supports students in deciding if their career choice is engineering. Consistent with my model that included concepts from Tinto's theory, retention was influenced by the student's revised commitment to an engineering career. Furthermore, Watson and Froyd's model suggested that engineering students must make the commitment to that of a professional engineer throughout their undergraduate education (Watson and Froyd, 2007).

It was found that enrollment in Engineering 110 was linked to a significantly higher college retention rate than not being enrolled in Engineering 110. The theory of both Tinto and Watson & Froyd supported that this was a causal relationship. In addition, students who enrolled in Engineering 110 but decided to transfer out of engineering, dropped out of the university at a rate less than 1%, suggesting that this course influenced them to continue their education at Michigan. Tinto has indicated that engagement in the classroom was especially important for freshman. Even though Engineering 110 is conducted in a large classroom, there is very good engagement between the students and senior faculty members in the engineering community. This could explain the low dropout rate of students who complete Engineering 110. The course is also known for demonstrating the excitement of an engineering career and it is conjectured that it is this excitement along with the engagement that makes a difference. Watson and Froyd (2007) suggested that career development into an engineer must be encouraged throughout the undergraduate years. Many students enter engineering college without the commitment to an engineering career. This course may help the student make the career commitment and therefore increases the retention. The following three conclusions were made with respect to enrollment in Engineering 110:

1. Engineering 110 was an effective intervention strategy that supported a higher retention rate
2. This research supported that some students benefit from both a high frequency of advising visits and enrollment in Engineering 110.
3. Some statistical evidence existed to support recruiting groups of students into Engineering 110 as a retention strategy.

Why Does Michigan Engineering have a High Retention Rate?

One of the objectives of this research was to explore why Michigan has a high engineering retention rate. Significant factors for high retention have been identified as high self-rating of math ability, high student performance in high school as measured by the high school rank, and low concern for financing a college education. The high school rank measured academic competitiveness, study habits and maturity in addition to academic preparedness. It is significant that high school rank was more important than either the high school GPA or the math placement test score. From the sensitivity analysis, it is clear that the freshman retention could decrease. However, the answer is not just with the incoming quality of students (high school rank and self-rating of math ability) and low concern about financing a college education. Courses like Engineering 110 can make a significant improvement in engineering college retention (4% difference in taking engineering 110 versus not taking it). As was stated earlier, engineering freshman retention and graduation rates were not available in the public domain of literature. If we assume the same relationship as in Figure 1-1 (see Figure 6-12 for a copy without the pointer to the University of Michigan), a drop in the freshman retention rate from 94% (the current retention rate) to 90% equates to a drop in the graduation rate of 85% to 76%.

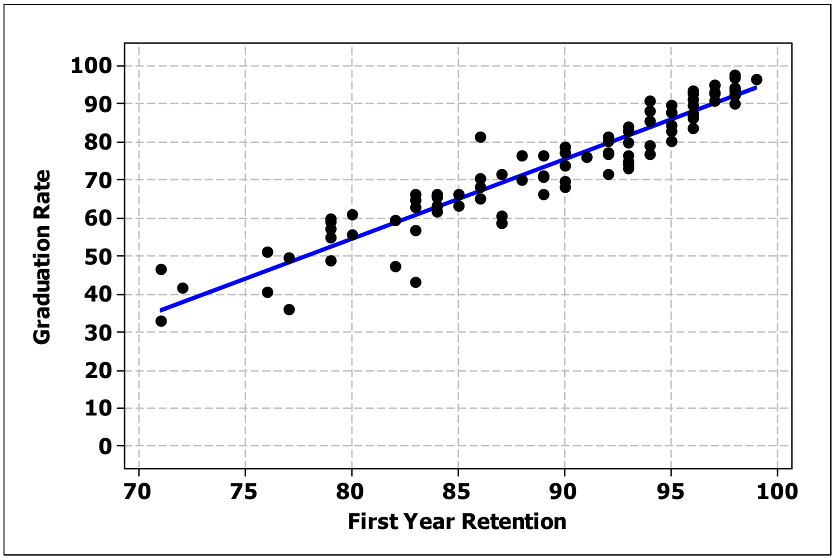


Figure 6-12: Graduation Rates vs. First Year Retention for Large Research Universities

Whereas a graduation rate of 85% is excellent, 76% is much less. The inference here is that Michigan Engineering has a high retention rate of 94% because it brings in excellent quality students AND has substantial interventions that "engineer student success." The sensitivity analyses provide more evidence that can be used to further engineer student success.

Goodness of Fit Statistics for the Logistic Regression

The comparison was made of the Unweighted Sum of Squares goodness of fit statistic, $\hat{S}$, to the Hosmer-Lemeshow (H-L) goodness of fit statistic. With the variability in the H-L by software package, the $\hat{S}$ statistic provided an alternative statistic for goodness of fit. With the application in this chapter, it detected influential outliers or long tails that were not consistent with the assumption of a logistic model for retention (and the H-L did not).

The disadvantage to the Ŝ is that it has not been incorporated into most statistical packages and requires a weighted regression run to determine the significance level. More research with alternative goodness of fit statistics is recommended.

Recommendations:

Based on these conclusions, the following recommendations related to engineering student retention are made:

- A high self-rating of math ability and a high school rank of 91% are good guidelines for college retention of engineering students. Some support programs should help develop an efficacy that supports a higher self-rating of students' math ability.
- Financial need is a significant predictor of retention and programs to assist students financially may be needed
- The Engineering 110 course is key to continued high retention. It should be expanded to service more engineering freshmen. The research suggests that student who visit the EAC (advising) at a high rate benefit from Engineering 110. It is recommended that a pilot program be implemented to further study the effectiveness of enrollment in Engineering 110 for students who need a high level of advising. In addition, it is recommended that an upper level career development course be considered.

Evidence suggests that retention of engineering students could be higher than it currently is with a stronger enrollment in Engineering 110 and continuation of the current support programs.

CHAPTER VII

COMPARISON OF THE ENGINEERING STUDENT SECTOR TO NON-ENGINEERING STUDENT SECTORS

A thesis of this research is that modeling of freshman engineering success is different from the modeling of the student success of other student sectors. This chapter explores these differences by comparing the Engineering sector to three non-engineering sectors:

1. Pre-med students
2. STM students (science, technology and math majors excluding engineering and pre-med students)
3. Non-STEM students (social science majors, humanity majors and business majors)

A description of each sector was given in Chapter III. The comparison of the Engineering sector to the other three sectors was made in three areas:

1. Multivariate comparisons of the pre-college characteristics. Two techniques were used: multiple comparisons across sectors for each pre-college characteristic and a discriminant analysis by sector using the pre-college characteristics.
2. An extension of the regression modeling of first year GPA to each of the four student sectors. Also, the STEM GPA was modeled using the factor scores for each. A comparison of first year GPA and STEM GPA distributions was made.
3. An extension of the logistic regression modeling of university retention to each of the four student sectors.

4. The special case of the subset of students who took Calculus I was discusses with respect to the comparison of the GPA and retention statistics.

This analysis can be stated in terms of the following hypotheses:

Different Pre-College Characteristics

1. A significant difference exists between the engineering sector and the other sectors in the distributions of pre-college characteristics.

Student Academic Success

1. The predictors for student success are different for the four sectors. The engineering sector will have more significant differences related to quantitative skills and confidence in quantitative skills.
2. F4 (Quantitative Skills) will be a significant predictor for student success
3. There will be differences in predictors of both the overall GPA and STEM GPA across student sectors.
4. Differences in first year GPA by gender and ethnicity will be explained by the significant predictors of student success.

University Retention

1. The predictors for university retention for the engineering sector will be different than the predictors for the non-engineering sectors.
2. Initial concern about financing college and the student’s first choice in college will be factors that influence university retention for all sectors
3. The university retention of students who enrolled in Calculus I will vary across sectors

Consistent with previous notation, factors from the factor analysis will be denoted by the Factor number, i.e. F1 and factors from an analysis of variance will be denoted by the factor’s name, such as gender.

This chapter is organized as follows. Section 7.1 includes all discussion of the methodology used in this chapter. The modeling of academic success (first year GPA) is consistent with the techniques used in Section 5.2. The modeling of university retention is consistent with the techniques used in Section 6.1. Section 7.2 examines multiple comparisons of the averages of the pre-college characteristics for the engineering sector to the non-engineering sectors. Section 7.2 also presents a discriminant analysis graph of the multivariate space of sectors. Section 7.3 compares the predictors of first year GPA and STEM GPA across student sections. Included in these regressions is the examination of significant interactions. Section 7.4 examines the differences in predictors of the university retention across sectors. Students enrolled in Calculus I are considered as a special case in Sections 7.5 and 7.6. Section 7.5 explores the comparison of the modeling of academic performance of students in Calculus I, since this is a gateway course into engineering. Section 7.6 examines the modeling of university retention of the Calculus I students. Finally, Section 7.7 summarizes the findings of this chapter.

7.1 METHODOLOGY

7.1.1 Multiple Comparisons and Discriminant Analysis

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 non-Engineering student sectors (Pre-med, STM and Non-STEM). If engineering student success is different from the student success of other student sectors, it is reasonable to hypothesize that there are significant differences among the sectors for the pre-college characteristics variables included in the model. To test this hypothesis, pairwise multiple comparisons were made on the four sectors with the pre-college characteristics. The Sidak multiple comparison technique, available with the SPSS 15.0 program was used. The Sidak test is a modified Bonferroni test and has a higher power than the traditional Bonferroni test. (Matthews, 2005) The family Type I error was set at .05. All records with an identified student sector of the 2004 cohort database were included in this analysis.

Nichols et al. (2007) compared STEM versus Non-STEM students for the CIRP survey variables by gender and ethnicity. They then identified the CIRP variables that were typically had high scores for STEM students. Significant variables for STEM students were the SAT math score, high school grades, self-ratings in computer skills, math ability and academic ability and a science orientation. The STEM students also scored high on deciding to go to college to get training for a specific career. The Non-STEM students scored high on several questions including the likelihood of changing a major field and career choice and participating in study abroad programs.

Because of the number of variables that showed a significant difference, a discriminant analysis further explored that the engineering sector presents a set of pre-college characteristics that are different than the other three student sectors. The objective of this discriminant analysis is to establish the most significant variables that defined the maximum possible distance between the centroids of the student sectors in the multivariate space. The centroids are the averages of the variables for each student sector. This is difficult to present graphically but the spacing between the centroids can be represented by the discriminant functions, often referred to as the canonical discriminant functions. The Unexplained Variance stepwise technique in Minitab 15.0 was used with a probability of an F to enter .05 (p-value) and to remove a p-value of .15. All the factor scores and deleted variables were initially entered into the discriminant analysis. Unequal Covariance matrices were assumed. The classification results table includes the accuracy of classification statistics; these were used as the measure of success of discriminant analysis prediction. For example, the accuracy of classifying a student as an Engineering student, was defined as the percent of engineering students who were correctly identified with the discriminant equation as engineering students. If more than five predictors entered the discriminant analysis, an improvement of at least 1% in the overall classification accuracy was required for the next predictor to enter. This criterion avoided entering predictors with a significant F to enter but contributed little to the final discriminant results. Canonical discriminant function plots are generated by the SPSS program and illustrate the centroids of the multivariate space of the four sectors. The discriminant analyses were conducted using the ACT subset of the 2004 cohort database.

7.1.2 Student Academic Success Modeling

Student academic success modeling of the engineering sector was discussed in Chapter V. This modeling is extended to the non-engineering sectors. In addition to the first year GPA, the first year STEM GPA is also modeled for all four student sectors. For consistency with the analyses in Chapter V, the data from the ACT subset for the 2004 cohort was used. No missing data among the factors were allowed.

For each regression, the following procedure was used:

1. A separate stepwise regression was run for each GPA as the dependent variables: first year GPA and first year STEM GPA.
2. The stepwise regression was run with the GPA as the dependent variable and the all the factor scores as the regressors. An F to enter at the .05 significance level was required.
3. For the significant ($p \leq .05$) factor scores, all two-way cross-products (interactions) were tested for significant at $p \leq .05$.
4. The significant cross-products and all the factor scores were again run in a stepwise regression to obtain the final regression equation.
5. The residuals from a regression should be approximately normally distributed. The probability plot of the residuals was checked for a normal distribution of the residuals.
6. The validity of the final regression was checked by reviewing the adjusted R^2, Mallows Cp and residual standard deviation. The change in R^2 for each step of the regression was check for an F-statistic that was significant at $p \leq .05$.
7. Multicollinearity among the independent variables can significantly bias the regression coefficients. To check multicollinearity, two measures recommended by Myers and Montgomery (2002) were used. VIF, the variance inflation factor was checked for a value less than 4.0 and the ratio of the maximum eigenvalue to the minimum eigenvalue was checked for a ration less than 100.

8. Once the regression coefficients were determined, the significant factor scores were entered into a generalized linear model to check for a significant difference in gender or ethnicity. The significant factor scores from the regression were treated as covariates in this generalized linear model.

In addition, a generalized linear model for both first year GPA and STEM GPA was considered combining all four student sectors. In this model, sector was a factor and all the factor scores were covariates. For the significant covariates, two-way cross-products were evaluated for significance ($p \leq .05$). Once the model was established, gender and ethnicity were added as factors to evaluate their effects on the model.

7.1.3 Student Retention Modeling

To address modeling of retention, logistic regression was applied. Consistent with the analysis in Chapter VI, the 2004 and 2005 cohorts were combined for the logistic regression. The stepwise logistic regression analysis conducted in Chapter VI for the engineering sector was extended to the non-engineering sectors and compared across sectors.

Comparison of retention rates for the four student sectors is made only for the university retention, the retention of the student in the university at one of its colleges. A stepwise logistic regression was run on each student sector with two groups: students returned to a college of the university for the 2nd year or students did not enroll in the university for the fall term of the 2nd year. The first year GPA and all pre-college characteristics were initially entered. The first year GPA was entered to be consistent with the model developed in Chapter II. Consistent with the methodology developed in Chapter VI, the Peduzzi et. al. rule of number of predictors is limited to the number of observations in the group of students who left the university divided by 10. The stepwise logistic regression was then rerun including only the significant predictors. In some cases, due to less missing data in the smaller subset of predictors, some of the predictors were no longer significant. Also, the Unweighted Sum of Squares goodness of fit statistic was calculated with the final run. After these models were developed, the effect of gender and ethnicity was tested for significance. Next, a logistic regression was run that included all four student sectors, with a factor for sector and all initially significant predictors included. The regression was verified by rerunning the regression with only the significant predictors. The effect of gender and ethnicity were then considered.

7.2 Pre-College Characteristics Comparison Among Sectors

7.2.1 Significant Pairwise Comparisons among Student Sectors

One of the research questions was whether there were differences in the averages of the pre-college characteristics among the four student sectors. For the initial set of pre-college characteristics (see Table 3-1), multiple comparisons were made comparing the average of the pre-college characteristic for the engineering sector to the average of the same pre-college characteristic for a non-engineering sector for the 2004 cohort. The significant differences are indicated in Table 7-1. The following variables showed no significant pairwise multiple comparisons between the engineering sector and the other three sectors: self-rating of cooperativeness, self-rating of leadership ability, self-rating of self-confidence (intellectual), hours per week in the past year spent talking to teacher outside of class, frequency of using the Internet for research or homework, frequency of studying with other students, frequency of tutoring another student, frequency of coming late to class, importance in deciding to go to college: to learn more about things that interest me, chance in the future to communicate regularly with your professors, importance in deciding to go to college: to be able to make more money; all the variables in Pillars P6. Commitment to this College, P7. Financial Needs, and P8. Family Support; self-confidence (social), hours per week in past year socializing with friends, hours per week in past year working (for pay), hours per week in past year student clubs/groups, chance in the future you will join a social fraternity or sorority, chance in the future you will play varsity/intercollegiate athletics, and chance in the future you will participate in student clubs/groups. The combined sample size for the multiple comparisons on the 2004 cohort for all sectors ranged from 947 to 1477 .

Table 7-1: Significant Differences in Pre-College Characteristics for the 2004 Cohort
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

Pre-College Characteristics	Engineering vs. Pre-Med	Engineering vs. STM	Engineering vs. Non-STEM
P1. High School Academic Achievement			
High school GPA			H
High school class rank			H
ACT composite	H	H	H
SATI total		H	H
Self-rating of academic ability			H
Self-rating of writing ability			L
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/week in past year spent studying/ doing homework	L		
Hours/week in past year spent reading for pleasure			L
Frequency of asking a teacher for advice after class	L		L
Felt overwhelmed by everything I had to do (frequency)	L	L	L
P4. Commitment to Career and Educational Goals			
Highest academic degree that you intend to obtain (recoded)	L		
Importance of going to college to get training for specific career			H
Importance of going to college: to prepare myself for graduate or professional school	L		
Chance in the future to change major field			L
Chance in the future to change career choice			L
Self-rating of drive to achieve	L		
Importance of: making a theoretical contribution to science			H
P5. Confidence in Quantitative Skills			
Self-rating of computer skills	H	H	H
Self-rating of mathematical ability	H	H	H
P8. Social Engagement			
Hours/week in past year playing video/computer games	H	H	H
Hours/week in past year partying			L
Hours/week in past year doing volunteer work	L		
Chance to participate in study abroad programs		L	L

Discussion of the Multiple Comparisons

The engineering sector had a significantly higher average ACT Composite, ACT Math , ACT Science, UM Math Placement Score, and UM Chemistry Placement Score than the other sectors (See Table 7-2). The Engineering sector also had significantly higher self-ratings in computer skills and mathematical ability, indicating a higher confidence in quantitative skills.

Table 7-2: Averages and Sample Sizes for Selected Pre-College Characteristics with Significant Differences (2004 Cohort)

Student Sector	ACT Composite Average	ACT Math Average	ACT Science Average	U-M Math Placement Average
Engineering	29.9 (n=265)	30.6 (n=268)	29.4 (n=268)	20.7 (n=333)
Pre-Med	28.3 (n=151)	28.5 (n=146)	27.1 (n=146)	16.9 (n=176)
STM	28.7 (n=235)	28.8 (n=241)	27.6 (n=241)	17.5 (n=288)
Non-STEM	28.3 (n=492)	27.7 (n=496)	26.5 (n=496)	15.7 (n=646)

Significantly, there were no differences in Commitment to attending this College, Financial Need or Family Support; indicating that all sectors perceived the same level of commitment to the university, financial need and family support. In the Study Habits pillar, the Engineering sector averaged a significantly lower level of "feeling overwhelmed" than the other student sectors. With respect to 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. The Engineering sector had less anticipation of participation in a study abroad program than the STM 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 showed a much stronger motivation with a significantly higher average for earning a higher degree and going to college to prepare for a graduate program. The Pre-Med students also showed a higher score on average number of hours per week studying or doing homework, and for participating in volunteer work.

The comparisons of the Engineering sector to the STM sector had 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 most significant differences occurred between the Engineering sector and Non-STEM sector. As previously discussed, the Engineering sector had significantly higher average for the ACT and SAT math scores and self-ratings of computer and mathematical abilities. In addition, the Engineering sector had significantly a higher average high school GPA and class rank and overall ACT/SAT scores. On career choice issues, the Engineering sector had a significantly higher level of importance attached to making a theoretical contribution to science, attached a higher importance of going to college to pursue a specific career and had a lower chance of changing careers . On the other hand, the Non-STEM sector had a significantly higher self-rating of writing ability, spent more time reading for pleasure, and significantly more likely to participate in a study abroad program. The Non-STEM students were more likely to talk to their professors. In socializing, the Non-STEM sector averaged more time in high school socializing with their friends and partying, while the Engineering sector averaged more time playing video and computer games.

The significant differences between the Engineering sector and Non-STEM sector were generally consistent with the Nicholls' study of differences between STEM and Non-STEM students.

7.2.2 Discriminant Analysis Results

Separation between the Non-STEM Sector and the "STEM" Sectors

Given the number of variables listed in Table 7-1 and the possibility of correlations among some of the variables, a stepwise discriminant analysis was used to identify significant characteristics that define the multivariate space for each of the four student sectors. Figure 7-1 displays the multivariate space of the four student sectors using the results of a four-sector discriminant analysis with the ACT subset. A separation between the Non-STEM sector and the other sectors which are usually considered as part of the "STEM" disciplines can be seen in Figure 7-1.

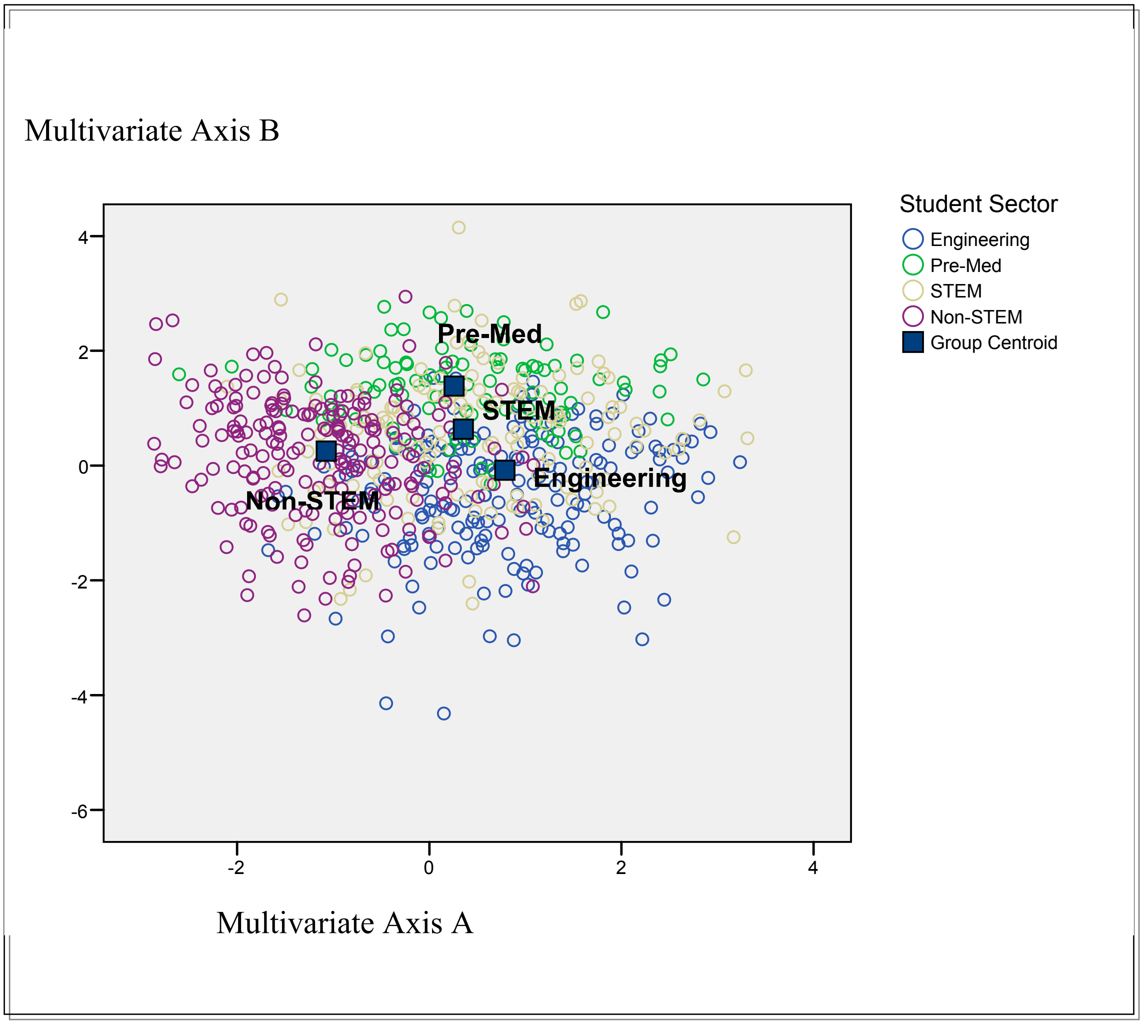


Figure 7-1: Multivariate Space Plot of Student Sectors Illustrates the Clustering of the STEM Disciplines Compared to the Non-STEM Sector (n=633)

For this analysis, both factor scores and the deleted variables were used. The significant predictors of the differences between sectors, in order of entering the discriminant analysis were:

1. Make a theoretical contribution to science
2. F9 (Educational Goals)
3. F11 (Confidence in Quantitative Skills)
4. F8 (Choice of Major and Career)
5. F4 (Quantitative Skills)
6. Self-Rating of Writing Ability

The variables "Make a theoretical contribution to science" and "Self-rating of writing ability" are variables that were deleted from the factor analyses. The overall classification accuracy was 58%. The Non-STEM sector has good discriminant distance from the other three sectors. However, the discriminant analysis had difficulty discriminating the STM group from the Pre-Med group. The first predictor, "Make a theoretical contribution to science" separated the Non-STEM sector from the other three sectors. The Pre-Med sector had the highest level for F9 (Educational Goals) since F9 (Educational Goals) is loaded with "highest academic degree aspiration" and Pre-med students are initially committed to a M.D. The engineering sector has the highest confidence in quantitative skills, even for the same ACT Math scores as students in another sector. F8 (Choice of Major and Career) tends to separate engineering and pre-med students from the STM and Non-STEM students since they are less likely to change majors or careers. The Engineering and STM sectors score high on quantitative skills and the Non-STEM sector scores high on writing ability.

Engineering Sector versus the Other Sectors Yields Interesting Discriminants

Because of the poor classification accuracy of 58% for the four sector discriminant analysis, a two-group stepwise discriminant analysis comparing the Engineering sector to the three non-Engineering sectors was conducted. This analysis gave much more positive results with an overall classification accuracy of 71% with a 76% classification accuracy for the engineering sector. The significant predictors for the two-group discriminant analysis were the same as the first three predictors in the four-sector discriminant analysis. They were:

1. F11 (Confidence in Quantitative Skills)
2. F9 (Educational Goals)
3. Important to make a theoretical contribution to science.

The model pillars related to P5 (Confidence in Quantitative Skills) and P4 (Commitment to Career and Educational Goals) were identified as the most significant for characterizing the Engineering student sector different from the non-Engineering student sectors. Even though the multiple comparisons showed significant differences in the ACT and SAT Math scores, which are included in the F4 (Quantitative Skills factor), F11 (Confidence in Quantitative Skills) was a more significant discriminant. In addition, one of the variables, "Important to make a theoretical contribution to science" was significant as a discriminant; this variable did not fit into the factor structure. In summary, Engineering sector students have a higher self-rating of their quantitative skills (math and computers) and express more of an orientation towards a science career than the non-Engineering sector students.

Using a binomial test for proportions, the classification accuracies are significantly higher than a 50-50 chance at a p-level of .000; therefore the discriminant analysis results indicate a significant improvement in prediction of the student sectors using the pre-college characteristics.

7.3 Comparison of Student Success Predictors

7.3.1 Predictors for First Year GPA- Results

The Astins' study (Astin, 1993) showed that engineering students had a GPA less than other students. For this research, the similar results were confirmed, with the engineering sector and Pre-Med sector with a GPA less than the STM and Non-STEM sectors. The distributions of the first year GPA are displayed in the form of box plots in Figure 7-2. A

Kruskal-Wallis test for equal medians confirmed a significant difference among the four sectors at p=.002.

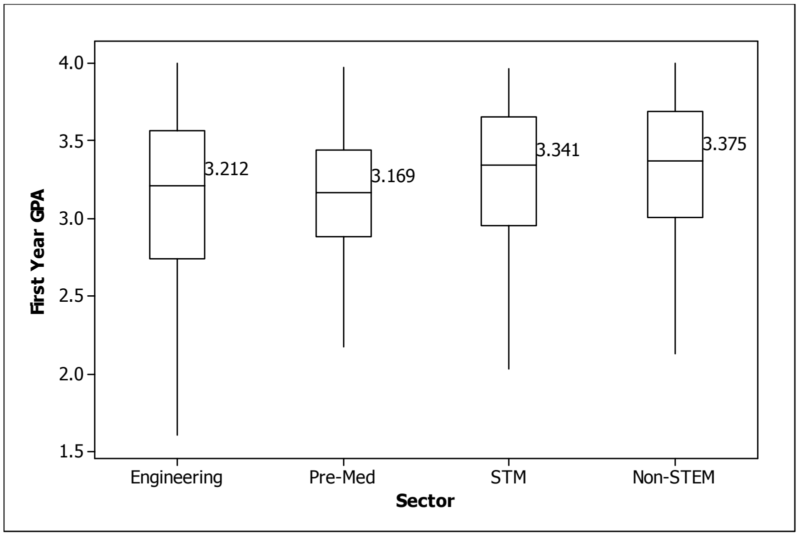


Figure 7-2: The Distributions for First Year GPA Are Significantly Different (See Table 7-3 for sample sizes)

Stepwise Regressions Results for First Year GPA Show Differences in Sectors

Table 7-3 displays the significant predictors for each of the four student sectors. The full regression tables are displayed in Appendix B. Table 7-4 displays the analysis of variance table for a generalized linear model on first year GPA, testing for differences among the student sectors with the factor scores as covariates.

No Significant Difference in Gender and Ethnicity Effects

When gender and ethnicity (URM status) are the only sources of variation besides sector in a generalized linear model, only 4% of the total variation is explained. Sector, gender and ethnicity are highly significant in a model with no covariates. When gender and ethnicity are added to the significant predictors of the model (in Table 7-3), gender and ethnicity are not statistically significant in a model that includes all sectors. The significance p-level for gender was .857 and for ethnicity was .143.

Table 7-3: Significant Predictors for First Year GPA for each Sector (p-level of t-test for regression coefficients)

Significant Factors	Engineering	Pre-Med	STM	Non-STEM
F1 High School Grades	.004	.025	.001	.000
F2 High School Performance		.000	.000	.000
F4 Quantitative Skills	.000			
F6 Study Habits Homework			.001	
F10 Career goals	.019			
F11 Confidence in Quantitative Skills	.017			
F17 Social Engagement Socializing			.008	
F15 Financial Needs			.028	
F19 Social Engagement -Activities		.049		.000
F1 x F4	.000			
F2 x F19				.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 (< 4.0)	1.193	1.014	1.066	1.025
Ratio of max/min Eigenvalue (<100)	6.97	1.71	2.54	1.58

Table 7-4: Generalized Linear Model for First Year GPA Including all Sectors Includes Covariates with p<.050. (n=635)

Tests of Between-Subjects Effects

Dependent Variable: First Year GPA

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	41.693[a]	9	4.633	25.119	.000	.266
Intercept	217.050	1	217.050	1176.927	.000	.653
Sector	7.419	3	2.473	13.409	.000	.060
F1_HSGrades	12.243	1	12.243	66.388	.000	.096
F2_HSPerformance	6.408	1	6.408	34.747	.000	.053
F4_Quantitative_Skills	.400	1	.400	2.171	.141	.003
F16_Family_Support	.907	1	.907	4.920	.027	.008
F19_SE_Activities	1.629	1	1.629	8.834	.003	.014
F1_HSGrades * F4_ Quantitative_Skills	2.974	1	2.974	16.125	.000	.025
Error	115.263	625	.184			
Total	6747.423	635				
Corrected Total	156.956	634				

a. R Squared = .266 (Adjusted R Squared = .255)

7.3.2 Discussion of the First Year GPA Regressions and Generalized Linear Model

The following findings are supported by Tables 7-3 and 7-4. :

- The set of selected pre-college characteristics, based on the model of engineering retention, explain more of the variation in the first year GPA for the Engineering sector data better than the non-Engineering sectors. The adjusted R^2 was 38% for the engineering sector compared to 15-28% for the non-engineering sectors. This compares to 29% in the Besterfield-Sacre et al. (1997) study for first term GPA and 21% for the Levin and Wyckoff (1988) study of freshman GPA.
- When the regressions were run separately for each sector, the significant regressors for first year GPA were different for each sector. The only common regressor among the four sectors is F1 (High School Grades). As expected, for the Engineering sector, F4 (Quantitative Skills), as measured by the math and science scores and the interaction effect of F1 (High School Grades) with F4 (Quantitative Skills) were more significant as regressors. For the non-Engineering sectors, overall academic achievement is very significant. F2 (High

School Performance) is very significant (p=.000). F2 (High School Performance) is the factor for overall academic ability as measured by the ACT Composite and self-rating of academic ability and was significant at p=.000 for all three non-engineering sectors.

- Two factors from P9 (Social Engagement Pillar) entered the regression equations for the non-Engineering sectors. This is supportive of Tinto's theory of retention (Tinto, 1993). F17 (Social Engagement-Socializing) was the factor associated with socializing, partying and social self-confidence. F19 (Social Engagement-Activities) was the factor associated with the chance in the future of a student being involved with college clubs, study abroad programs and playing video games).
- The regression of the STM sector was the only sector that found support for F6 (Study Habits- Homework) as a strong predictor of first year GPA.
- Several cross-product interaction effects were found to be significant regressor (see Table 7-3). This supported the hypothesis of interaction effects for student success.
- Because of the values of the VIFs and the ratio of the largest to smallest eigenvalues, there was little concern about multi-collinearity biasing the regression coefficients.
- The generalized linear model represented a model of first year GPA for the entire freshman class. The partial eta squares indicated that F1 (High School Grades) and F2 (High School Performance) from the first pillar P1 (High School Academic Achievement) dominated and provided the most contribution to explaining the total variation in first year GPA across all sectors.
- The same variables that were significant in the regression were also significant in the generalized linear model. In addition, F16 (Family Support) became a significant covariate (p=.027).
- A significant difference of the average first year GPA among the four student sectors existed (F-statistic = 13.4, p=.000 for Sector in Table 7-4), even after adjusting the averages for the significant covariates in the model. This suggested

that each student sector needed its own model for effective student success strategies and policies.

- In the combined analysis using a generalized linear model, F4 (Quantitative Skills) was not significant but because the F1 (High School Grades) x F4 (Quantitative Skills) interaction was, and using the hierarchy rule, it was included as a covariate. The hierarchy rule in design of experiments states that if an interaction term is present in a model, the main effects must be also.
- With only gender and ethnicity in a model for first year GPA, less than 5% of the total variation in first year GPA is explained. The differences in the first year GPA by ethnicity was highly significant. Once the covariates were entered into the model, there was no statistically significant difference in the average first year GPA due to differences in gender or ethnicity (URM and Non-URM); this finding suggested that the significant pre-college characteristic covariates explained the differences in the average first year GPA by gender and ethnicity.

7.3.3 Predictors for First Year STEM GPA - Results

The first year STEM GPA is a second measure of student success. The STEM GPA was defined as the GPA of all freshman level science, math and engineering courses (Chapter 3). In this section, statistics and graphs will be presented to better understand the first year STEM GPA. Then the regression results for each sector will be presented along with the generalized linear model for the entire freshman class.

Understanding the STEM GPA

For a comparison by sectors of the frequency of enrollment in STEM courses, Table 7-5 tabulates the number of students who enrolled in the more common STEM courses by student sector.

Engineering is often considered similar to the other STEM disciplines. On the average, engineering students enroll in six STEM courses in the freshman year compared to three to four courses for Pre-Med and STM students. (Some engineering students enroll in sophomore level STEM courses.) 45% of the non-STEM students enroll in no freshman level STEM courses.

Table 7-5: Number of STEM Courses by Sector

Course	Engineering	Pre-Med	STM	Non-STEM
N	184	100	145	206
Biol 162	12	62	25	9
Chem 130	69	74	41	13
Math 115	40	43	42	29
Math 116	61	23	29	7
Physics 140	65	7	26	4

Figure 7-3 plots the empirical cumulative distributions of both the first year STEM GPA and (overall) first year GPA for all four sections. Figure 7-3 (top figure) shows that the engineering sector has the highest STEM GPA distribution of the four sectors. This pattern is reversed in the bottom figure with the engineering sector having the highest percent of students with a GPA < 2.5. Using the Kruskal-Wallis test, there was a significant difference in the distributions for the four sectors for both the overall GPA and STEM GPA ($p<.002$).

The STEM GPA includes only the freshman level STEM courses. With the lower overall GPA, academic probation may be more likely for engineering students than for other students. This difference will be explored in more detail in this chapter's discussion, section 7-7.

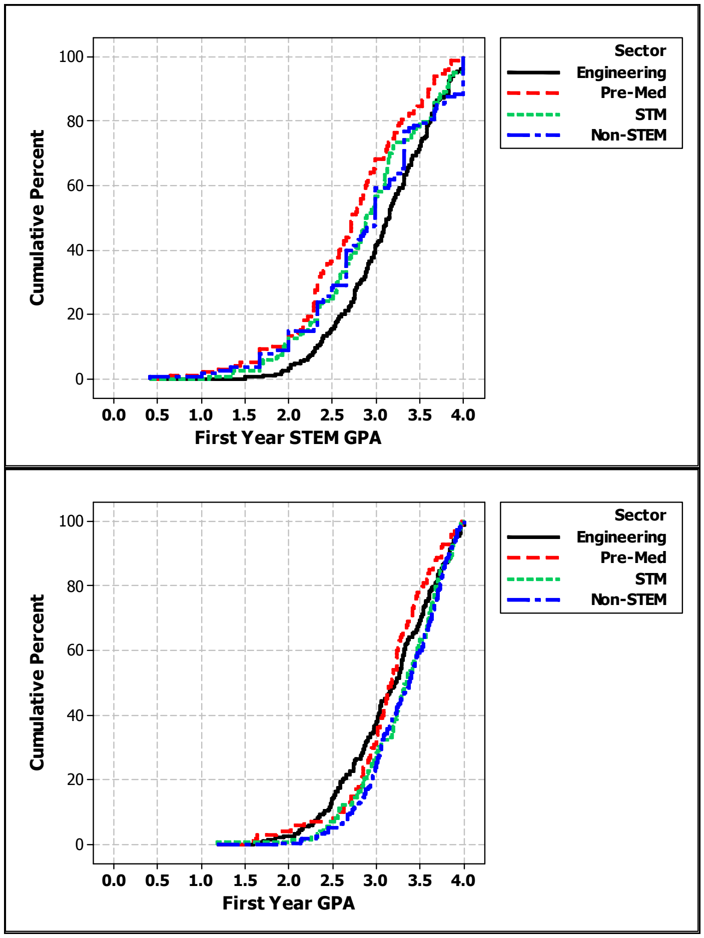


Figure 7-3: Cumulative Distributions of the First Year STEM GPA (top) and First Year GPA (bottom) by Student Sector (sample sizes are the same as in Tables 7-3 and 7-6)

Stepwise Regressions and Generalized Linear Model for First Year STEM GPA Show Consistency

Table 7-6 presents the stepwise regression results while Table 7-7 presents the generalized linear model results. The full regression tables are in Appendix D.

Table 7-6: Significant Predictors for First Year STEM GPA for each Sector (p-level of t-test for regression coefficients)

Significant Factors	Engineering	Pre-Med	STM	Non-STEM
F1 High School Grades	.000		.010	.004
F2 High School Performance			.027	
F4 Quantitative Skills	.000	.000	.037	.000
F9 Educational Goals				.016
F10 Career Goals	.001			
F11 Confidence in Quantitative Skills	.001			
F15 Financial Needs			.025	
F1 x F4	.000			
F1 x F11	.036			
Number of cases	184	98	120	113
Adjusted R^2	0.48	0.17	0.30	0.31
Mallow's Cp	1.0	9.7	6.0	10.1
Maximum VIF (< 4)	2.317	1.000	2.272	1.036
Ratio of max/min Eigenvalue (<100)	9.64	1.39	7.27	1.65

Table 7-7 Generalized Linear Model for First Year STEM GPA (n=515)

Tests of Between-Subjects Effects

Dependent Variable: First Year STEM GPA

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	76.465[a]	7	10.924	37.364	.000	.340
Intercept	3671.066	1	3671.066	12556.910	.000	.961
Sector	1.985	3	.662	2.263	.080	.013
F1_HSGrades	10.525	1	10.525	36.001	.000	.066
F2_HSPerformance	3.153	1	3.153	10.786	.001	.021
F4_Quantitative_Skills	8.340	1	8.340	28.525	.000	.053
F11_Confidence	1.977	1	1.977	6.763	.010	.013
Error	148.224	507	.292			
Total	4670.691	515				
Corrected Total	224.689	514				

a. R Squared = .340 (Adjusted R Squared = .331)

All the sectors include F4 Quantitative Skills as a significant predictor in the regression of the STEM GPA. This was explored in more detail. Figure 7-4 shows a plot of STEM GPA versus F4 for each sector. Note that the patterns are very consistent with the engineering sector having the least variation about the regression line; its adjusted R^2 was 33% just for F4.

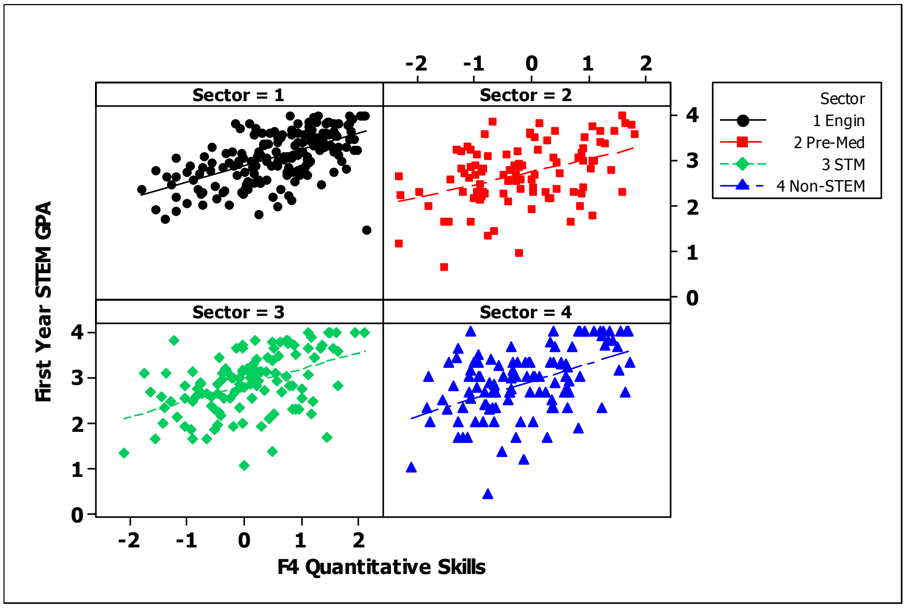


Figure 7-4: First Year STEM GPA versus F4 (Quantitative Skills). Sample sizes are the same as in Table 7-8)

The consistency in the slope of the regression lines across sectors is noteworthy. Comparison of the slopes of the regression lines in Figure 7-4 showed no significant difference among the sectors. (See Table 7-8)

TABLE 7-8: Comparison of Slopes of F4 on First Year STEM GPA Show No Difference

Student Sector	Regression Coefficient for F4 Quantitative Skills (Slope)	95% Lower Confidence Limit	95% Upper Confidence Limit	N	Adjusted R^2
Engineering	0.357	0.283	0.430	184	0.33
Pre-Med	0.286	0.160	0.412	98	0.17
STM	0.354	0.231	0.476	120	0.21
Non-STEM	0.387	0.257	0.517	113	0.23

7.3.4 Discussion of the STEM GPA Regressions and Generalized Linear Model

The following findings are supported by the regressions for first year STEM GPA:

- With the STEM GPA regressions, there was more consistency across sectors.
- F4 (Quantitative Skills) was the most significant covariate for all four sectors. F1 (High School Grades) was also a strong predictor.
- There was no statistically significant difference in the slopes of first year STEM GPA versus F4 (Quantitative Skills). (Table 7-8)
- For the engineering sector, with only F4 (Quantitative Skills) in the model, 33% of the total variation in STEM GPA was explained. With all the covariates, 48% of the total variation in STEM GPA was explained.
- Concern about financing a college education was significant only for the STM sector

The generalized linear model supports the following findings for first year STEM GPA:

- The STEM GPA is a more consistent measure across all student sectors. Once the covariates are taken into account, there is no significant difference among the sector averages of STEM GPA ($p=.080$).
- When F4 (Quantitative Skills) is included in the model, there is no significant difference in average first year STEM GPA among sectors.
- Four factor scores explained 33% of the total variation in STEM GPA for the entire freshman cohort: F1 (High School Grades), F2 (High School Performance), F4 (Quantitative Skills) and F11 (Confidence in Quantitative Skills). This provides strong support for the importance of strong STEM preparation in high school.
- When Gender and Ethnicity (URM status) are the only sources of variation besides sector in a generalized linear model, only 7% of the total variation is explained. In this case, sector, gender, and ethnicity are highly significant ($p<.004$). When gender and ethnicity were added to the covariate model in Table 7-7, gender and ethnicity are not statistically significant effects. The significance probability level was .243 for gender and .946 for ethnicity with an adjusted R^2 at

33%. The covariates explain the differences in the average first year STEM GPA by gender and ethnicity.

7.4 Comparison of Predictors of University Retention

In this section, descriptive statistics of the university retention by student sector are presented. The freshman year is seen as a year of transition and the pursuit of an academic degree is the important issue. It is reasonable to expect some students to transfer to other colleges within the university. The complement of university retention is the dropout rate (from the university). To minimize loss to society of human potential, the dropout rate ideally needs to be close to zero.

Note on Sample Size:

For this analysis, the 2004 and 2005 cohorts were combined. For the comparison analyses by student sector, the sample size was 3287. The sample sizes for each student sector are displayed in Table 7-9 of Section 7.4.1 Results. For the Pareto chart of retention by probably major, the sample size was 3275. The ACT and SAT subsets were not considered in this analysis.

7.4.1 Results

Summary Statistics for the University Retention Rates

Table 7-9 and Figure 7-5 shows the University Retention Rates for each Sector. Figure 7-6 shows the university retention rate by student major for those majors that had at least 30 students (to avoid small sample size bias). All the engineering majors have university retention greater than 95%.

Table 7-9: University Retention Rates for Each Student Sector Show a High Retention Rate for All Sectors

Student Sector	Students Returned	Students Not Enrolled	Total	University Retention (%)
Engineering	717	18	735	97.6
Pre-Med	417	17	434	96.1
STM	599	29	628	95.4
Non-STEM	1437	53	1490	96.4
All Sectors	3170	117	3287	96.4

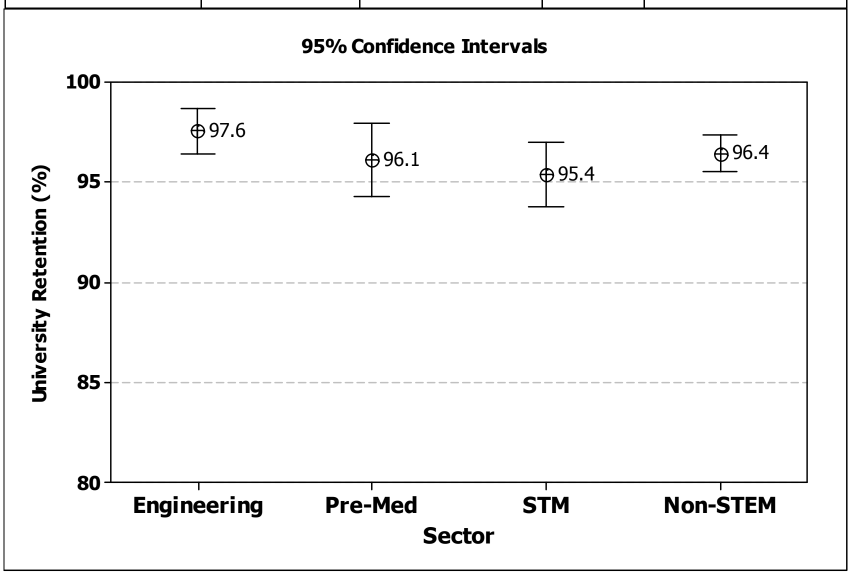


Figure 7-5: No Significant Difference in University Retention Rates by Sector Using 95% Confidence Intervals on University Retention (n=3287)

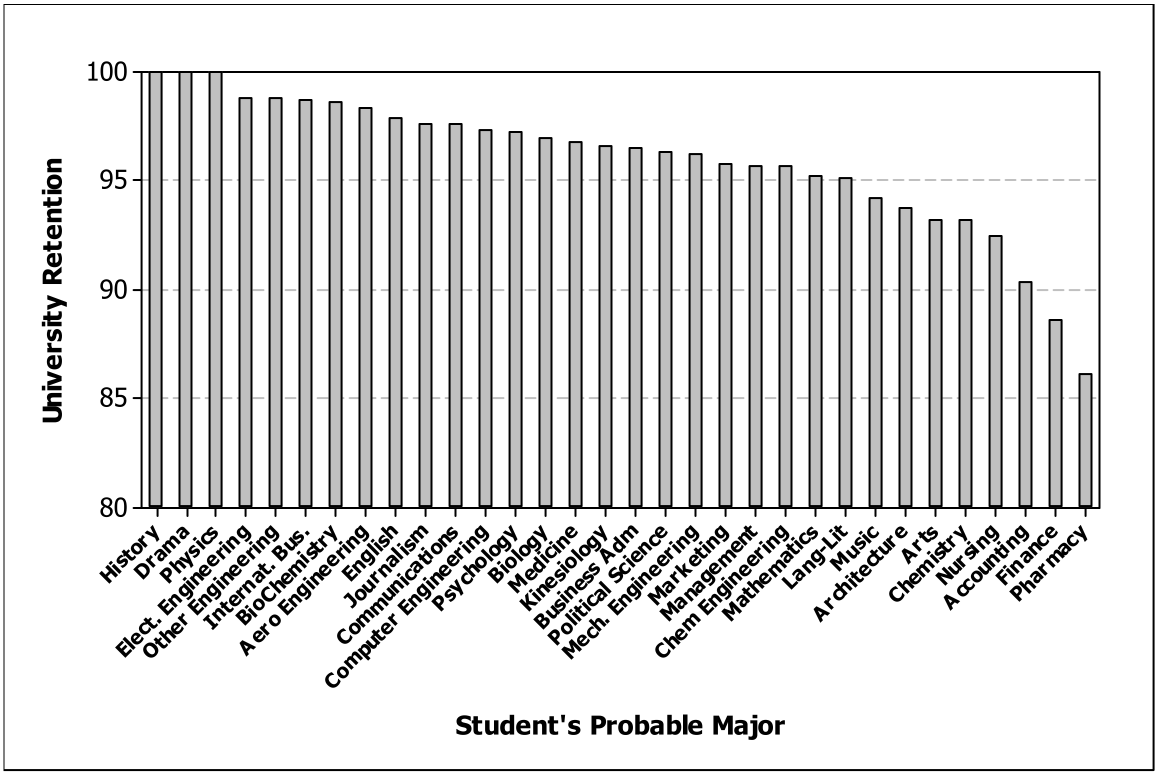


Figure 7-6: Pareto Chart of University Retention by Probable Major at Freshman Orientation (n= 3275)

Predictors of University Retention

Table 7-10 displays the significant predictors for university retention from the logistic regressions. For the Non-STEM sector, there is disagreement between the H-L goodness of fit statistic and the unweighted sum of squares statistic. A plot of influential points indicates that when three influential points with a GPA < 1.5000 were deleted from the analysis, the GPA is no longer a significant predictor ($p=.158$). A review of the data indicates that the high school rank is not a predictor either. An attempt was made to rerun the stepwise logistic regression with all the pre-college characteristics (as described in Section 7.1), and three variables were significant: Concern about finances, Self-rating of creativity and Self-rating of writing ability. Due to all the variables entered, the sample size was only 478 out of 1487 data points (due to missing data). When only these three variables were entered into the regression, the sample size was 1431, but none of the variables were significant. Concern about finances was the most significant with $p=.062$.

Thus, the attempts to find a consistent predictor without the three influential points, led to the conclusion that no consistent predictor existed in this set of variables. This led to the conclusion that the university retention of the Non-STEM sector was best described by a constant model of Probability of retention =0 .966.

Table 7-10: Logistic Regression Models

Significant Pre-College Predictor	**Engineering Sector Coefficient (p-level)**	**Pre-Med Sector Coefficient (p-level)**	**STM Sector Coefficient (p-level)**	**Non-STEM Sector Coefficient (p-level)**
Constant	-10.187 (p=.004)	-2.053 (p=.074)	-1.488 (p=.091)	0.837 (p=.345)
First Year GPA		1.787 (p=.000)	1.515 (p=.000)	0.760 (p=.006)
High School Rank	0.177 (p=.000)			
Concern about Finances	-1.386 (p=.002)			
Unweighted Sums of Squares Z-Score (p-level)	.121 (p=.548)	-0.679 (p=.248)	0.270 (p=.603)	-3.929 (p<.005)
Hosmer- Lemeshow Test (p-level)	8.775 (p=.187)	6.594 (p=.581)	4.227 (p=.836)	9.891 (p=.273)
Sample Size	705	433	626	1490

The first year GPA, high school rank and concern about finances were entered into a stepwise logistic regression along with a variable for sector. Table 7-11 displays the logistic regression for university retention with the entire freshman class (i.e. all four student sectors).

Table 7-11: Logistic Regression Table for University Retention (All Student Sectors, n=3199)

Source	d.f.	B	S.E.(B)	Wald	p-level	Odds Ratio (Exp (B))	95% C.I. on Odds Ratio	
							Lower	Upper
First Year GPA	1	1.269	0.159	63.82	.000	3.558	2.606	4.857
Concern about Finances	1	-0.474	0.158	9.033	.003	0.622	0.457	0.848
Sector	3			9.59	.022			

Overall, the first year GPA was a better predictor across all sectors than the high school rank. Since first year GPA and concern about finances were significant, the retention rate is plotted by GPA in Figure 7-7. (The sample sizes are shown in Table 7-12). Confidence intervals by GPA and concern about finances are displayed in Figures 7-8 and 7-9. Most of the variation in retention among the sectors occurs when the GPA is less than 2.0. There are no significant differences based on comparing the confidence intervals.

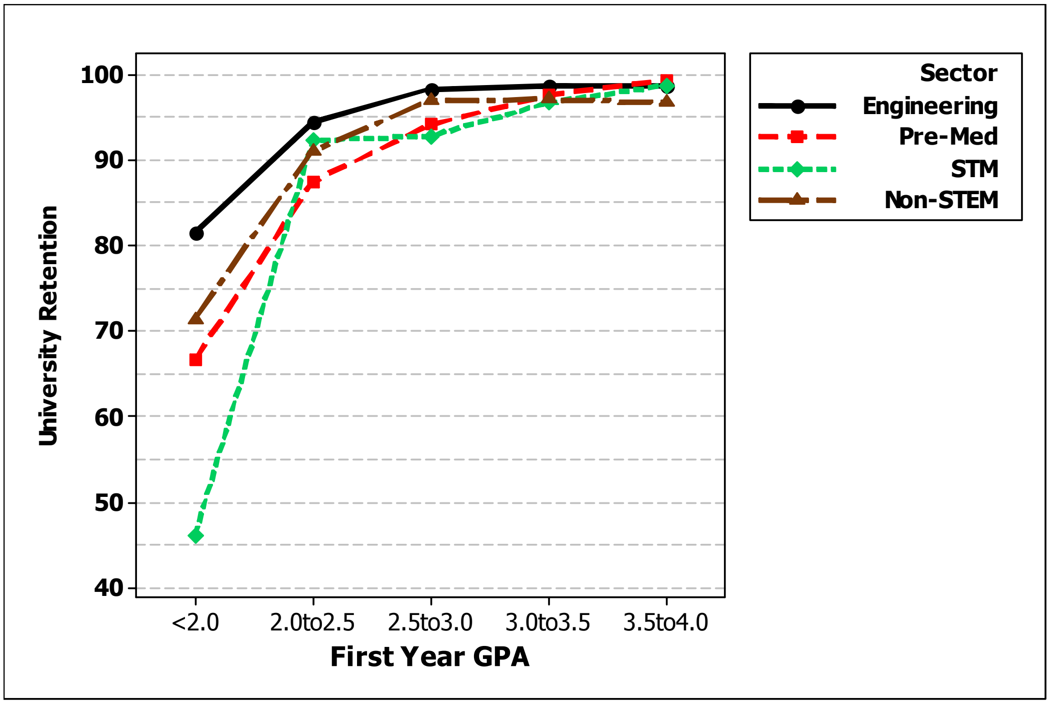


Figure 7-7: University Retention by Half-Grade Intervals of GPA for all Sectors

Table 7-12: Sample Sizes Associated with Figure 7-7 and Figure 7-8

First Year GPA	Sector			
	Engineering	**Pre-Med**	**STM**	**Non-STEM**
< 2.0	27	12	13	14
2.0 to 2.5	72	24	39	56
2.5 to 3.0	182	85	125	264
3.0 to 3.5	230	171	212	555
3.5 to 4.0	224	142	239	601
Total	735	434	628	1490

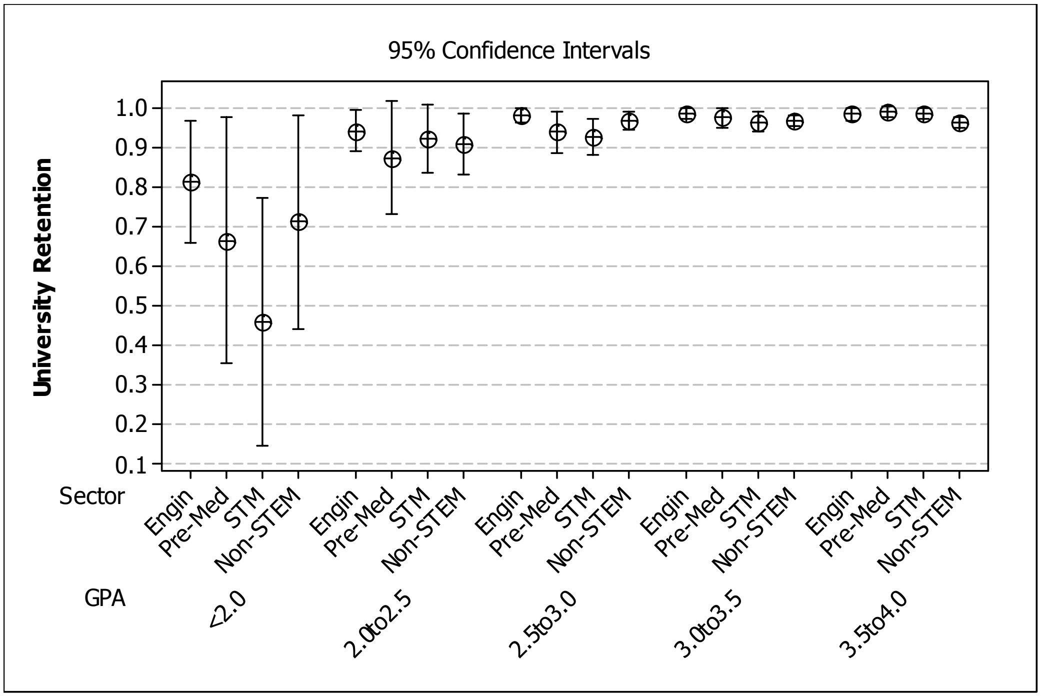


Figure 7-8: 95% Confidence Intervals on University Retention by GPA Interval

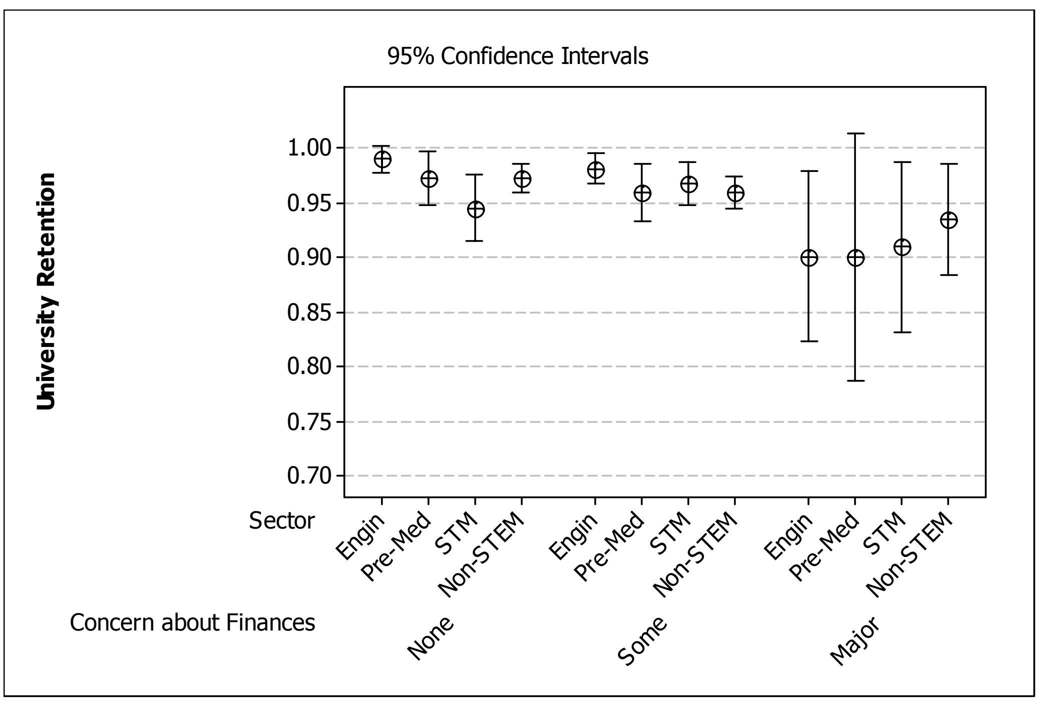


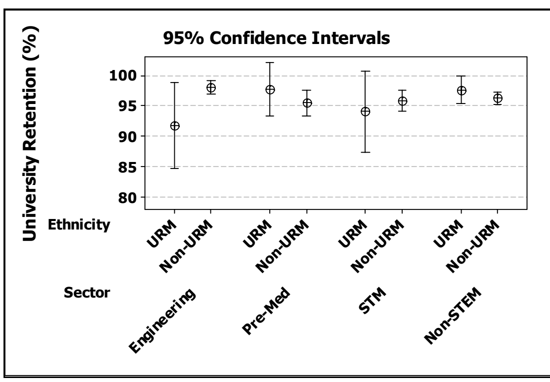
Figure 7-9: 95% Confidence Intervals on the University Retention by Level of Concern about Finances (See Table 7-13 for sample sizes)

Table 7-13: Sample Sizes for Figure 7-9

Concern About Finances	Sector			
	Engineering	Pre-Med	STM	Non-STEM
None	290	179	218	656
Some	369	219	336	700
Major	60	30	55	92

No Significant Difference by Gender and Ethnicity for University Retention

When confidence intervals on the university retention by gender and ethnicity were calculated, there was no significant difference in ethnicity within student sector of gender within student section (see Figure 7-10) When gender and ethnicity were entered into the logistic regression models discussed in this section, there was no significant difference in gender or ethnicity.



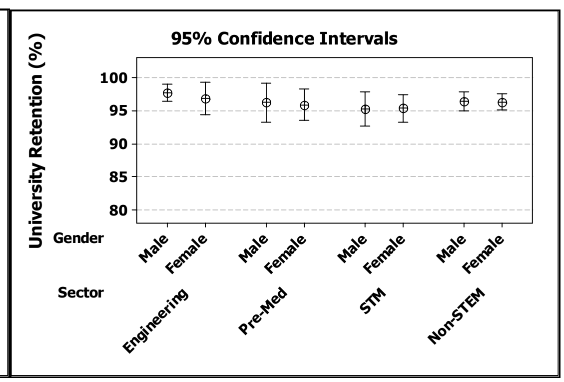


Figure 7-10: No Significant Difference in University Retention by Ethnicity (left) or Gender (right) as shown by 95% Confidence Intervals on the University Retention

Because of the interest in retention for female and underrepresented minority students, Figures 7-11, 7-12 and 7-13 show the university retention for female students, male students and under-represented minority students, respectively. The sample sizes for Figures 7-10 through 7-13 are shown in Table 7-14.

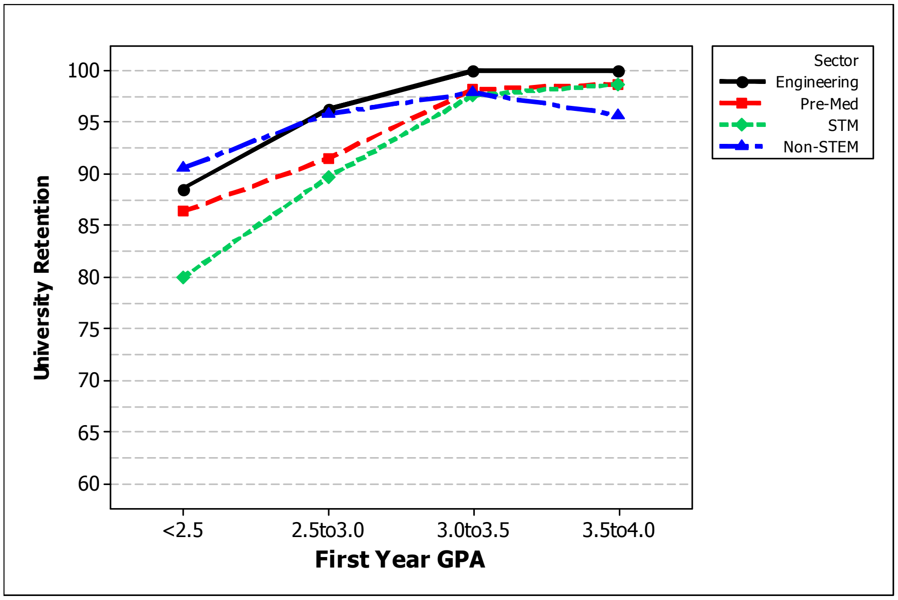


Figure 7-11: University Retention by Sector and GPA Category for Female Students

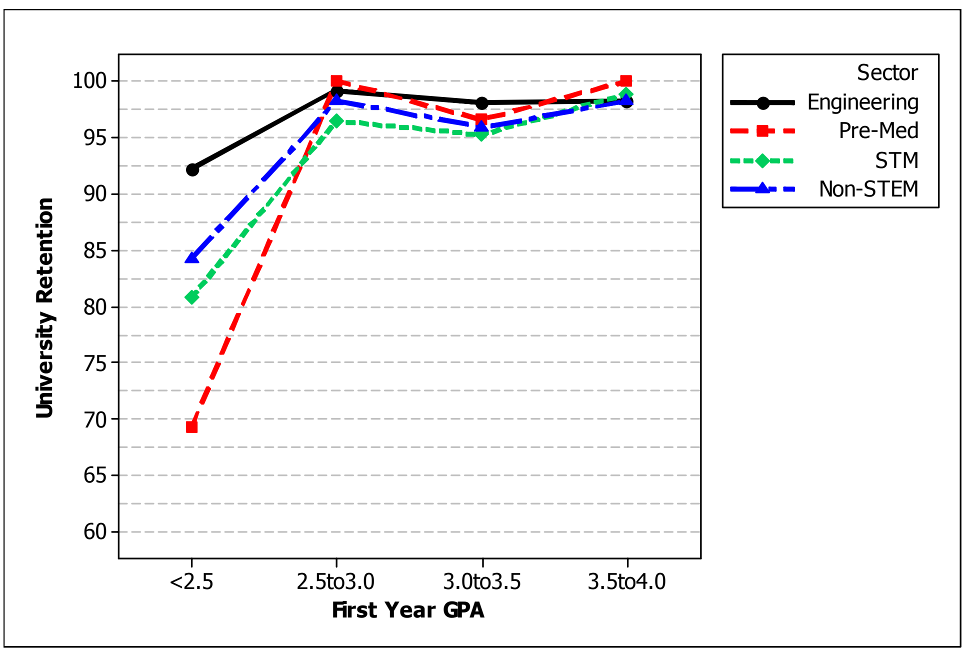


Figure 7-12: University Retention by Sector and GPA Category for Male Students

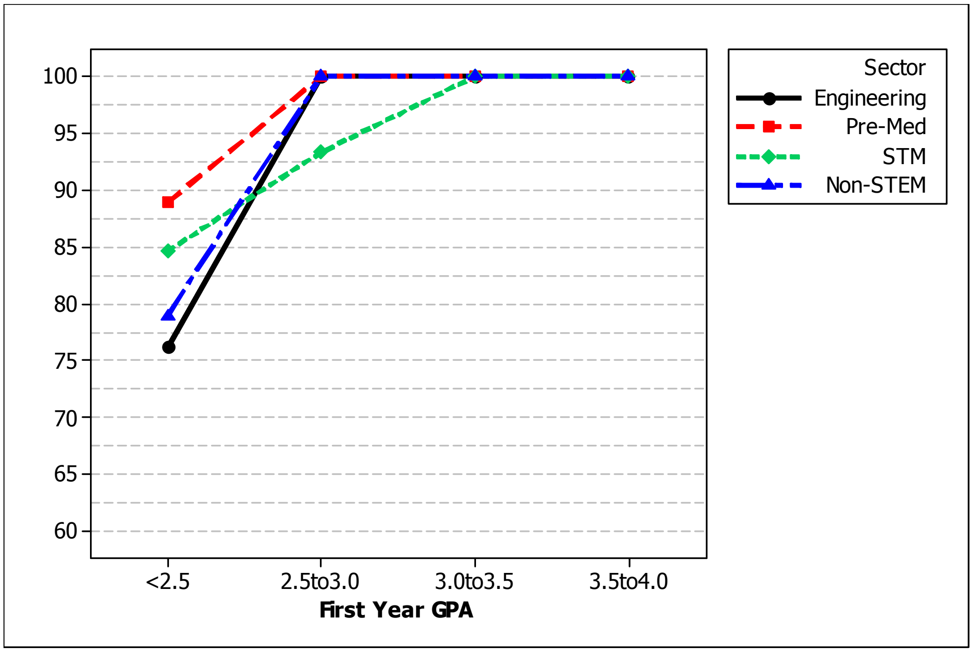


Figure 7-13: University Retention by Sector and GPA Category for Under-represented minority students

Figure 7-11 displays the university retention for female students; compared to male students, female students appear to factor GPA more into their decision as to whether to stay in the university. Note that the engineering sector has the highest university retention rates. Both Figure 7-12 and Figure 7-13 show close to 100% retention for a first year GPA > 2.5 for both male students and URM students. The most variability occurs with the GPA < 2.5. 95% confidence intervals show no significant differences between sectors for any of the GPA intervals, including a GPA< 2.5.

Table 7-14: Sample Sizes Associated with Figures 7-12, 7-13, 7-14 and 7-15

Gender or Ethnicity	First Year GPA	Sector			
		Engineering	Pre-Med	STM	Non-STEM
Gender					
Male	<2.5	64	13	26	38
	2.5 to 3.0	127	26	57	118
	3.0 to 3.5	165	59	84	221
	3.5 to 4.0	179	62	89	225
	Total	535	160	256	602
Female	<2.5	33	22	25	32
	2.5 to 3.0	53	59	68	144
	3.0 to 3.5	62	111	127	330
	3.5 to 4.0	43	79	150	374
	Total	193	271	370	880
Ethnicity					
URM	<2.5	21	9	13	19
	2.5 to 3.0	22	18	15	48
	3.0 to 3.5	10	13	13	58
	3.5 to 4.0	8	6	10	50
		61	46	52	175
Non-URM	<2.5	74	23	32	46
	2.5 to 3.0	148	63	106	208
	3.0 to 3.5	205	148	184	466
	3.5 to 4.0	194	129	216	513
		621	363	538	1233

7.4.2 Discussion

When university retention was considered, there was a difference in significant predictors for the engineering sector versus the non-engineering sectors. In Chapter VI, high school rank was a more significant predictor for the engineering sector than the first year GPA.

In this chapter, it was found that the first year GPA was a strong predictor for the Pre-Med and STM sectors. Neither the GPA nor the high school rank was a strong predictor for the Non-STEM sector. When the four sectors were combined, both first year GPA and concern about finances were strong predictors for university retention (Table 7-11). There was no difference in university retention by gender or ethnicity across sectors, for a given GPA interval.

7.5 Special Case: Comparison of Student Success for Students Enrolled in Calculus I as First Math Course

This section and section 7.6 look at the subset of students who enroll in Calculus I as their first course in freshman engineering. In the 2004 cohort, 30% of the students were enrolled in Calculus I. In a competitive grade environment, they are most at risk for academic success and, in general, may have more challenges for freshman retention. The analysis is similar to that of the entire freshman class for academic success (Section 7.3) and student retention (Section 7.4). The analysis sample for academic success in this section is the ACT subset for the 2004 cohort.

7.5.1 No Difference in the Calculus I Grade Distributions

One of the research questions is whether engineering students earn better grades than non-engineering students in Calculus I (Math 115). Figure 7-14 shows the box plots of the grade distributions each student sector. Included in these distributions were students who were full time freshmen enrolled in Calculus I as their first course in math during the freshman year for the 2004 cohort. The engineering sector shows a tighter distribution. In this time period, the College of Engineering had invited some students who were struggling academically in Calculus I to transfer to Pre-Calculus after the first midterm of Calculus and these students would not have completed Calculus I. (This program was discussed in Koch and Herrin, 2006.) This may explain the tighter distribution. Using the Kruskal-Wallis test, there was no statistically significant difference in these distributions. In terms of preparation levels, there were no significant differences in the ACT math scores.

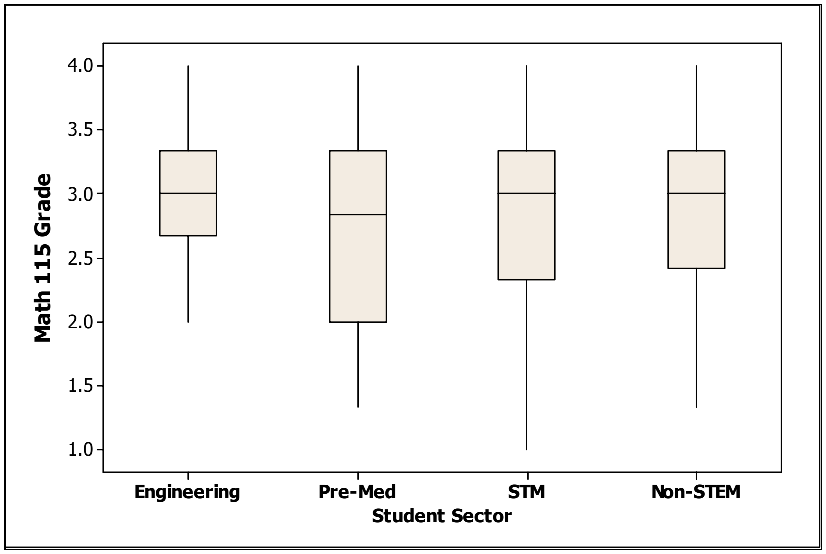


Figure 7-14: Box Plots of Calculus I Grade by Sector Show No Significant Differences (combined sample size equals 179)

7.5.2 Comparison of Calculus I Students for STEM GPA and Overall GPA

One of the research questions is whether engineering students earn a better or worst first year GPA and STEM GPA than non-engineering students. On the one hand, engineering students have higher average admissions scores (see Table 7-1). On the other hand, the freshman engineering courses are considered very competitive. Figure 7-15 displays the cumulative distribution for the STEM GPA (only freshman STEM courses) and the overall first year GPA.

Explicit differences exist between the two figures. Figure 7-15 (top) showed no significant difference among the four distributions for STEM GPA. In Figure 7-15 (bottom), this trend was reversed with a significant difference between the distributions of the sectors. The engineering student distribution has the largest left (lower) tail with 18% of the engineering students earning an overall GPA less than 2.5 compared to 13% for STM sector and 4% for the Pre-Med and Non-STEM sectors. The Kruskal-Wallis (non-parametric) test was used to determine significance.

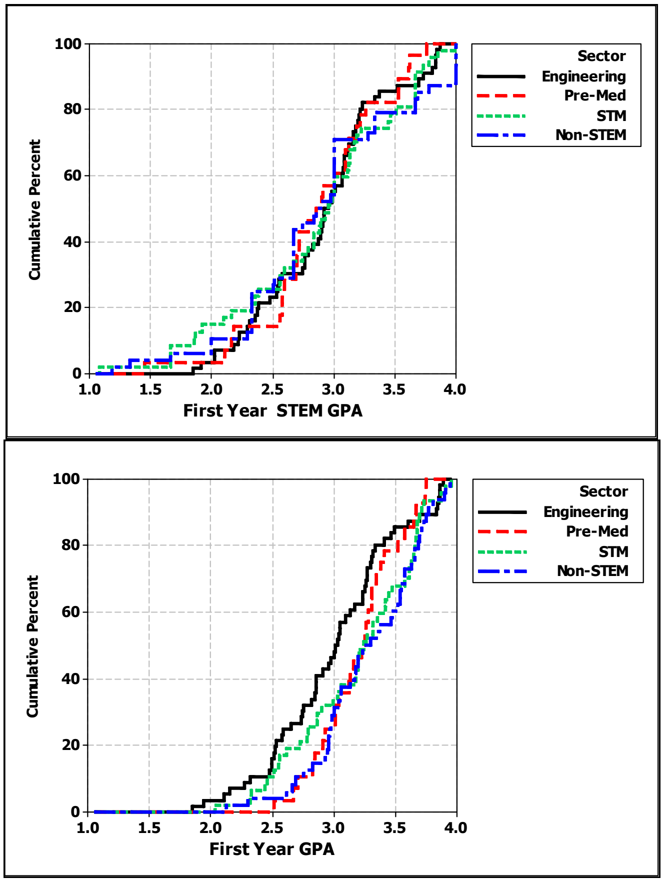


Figure 7-15: Cumulative Distribution of First Year STEM GPA (top) and First Year GPA (bottom) for Calculus I Students Show Differences in Sectors . The combined sample size for both figures is 179.

7.5.3 Discussion

The data supported that there was no significant difference in the distribution among student sectors of either the preparation level (ACT math score) or performance in the Calculus I course. Although the engineering sector had higher average ACT and SAT scores, the students who enrolled in Calculus I were placed in this course with the math placement test. My hypothesis of a significant difference in the STEM GPA distributions among the four student sectors was not verified but my hypothesis of a significant difference in the overall GPA distribution was verified. For students whose first course was Calculus I, the engineering students' grade distribution of the first year GPA had the lowest average, and 18% of the students earned a predicted first year GPA less than

2.500. Since the same trend existed for all freshmen and students who took Calculus I, the only logical explanation of this reversal of distributions in Figure 7-15 is that the STEM courses are more competitive than the non-STEM courses.

7.6 Special Case: University Retention Rates of Calculus I Students

As a continuation of a study of Calculus I students, this section compares the freshman retention rates by student sector. The analysis sample is the combined 2004 and 2005 cohorts.[6]

7.6.1 Results

Figure 7-16 displays the 95% confidence intervals on the university retention for each student sector.

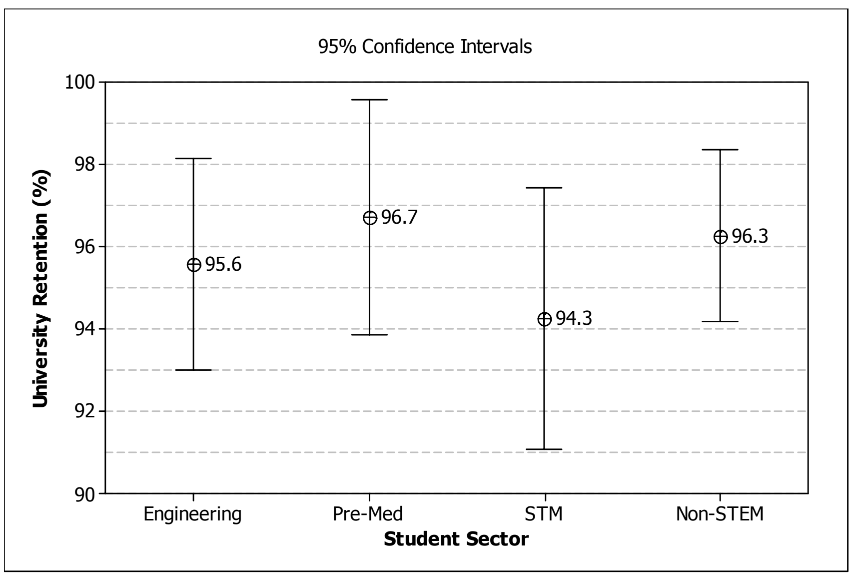


Figure 7-16: No Difference in Retention Among Sectors for Calculus I Students (combined sample size equals 930)

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[6] Students who initially enrolled in Calculus I (Math 115) or Pre-Calculus (Math 110) were included in this sample since most of the Math 110 students started in Math 115.

7.6.2 Discussion

For students who enrolled in Calculus I (Math 115), there was consistency across the four student sectors for university retention. The confidence intervals in Figure 7-16 showed no significant difference in retention rates. In addition, all four confidence intervals include 96.4, the university retention rate for all sectors, supporting that the retention rates were statistically the same. Since Calculus I is a gateway course for engineering, the fact that the retention of the Calculus I students in engineering is the same as other student disciplines is significant information for retention policies.

7.7 Summary and Recommendations

7.7.1 Summary of Hypotheses

In understanding engineering student success and retention at a university, it is important to look at the surrounding environment and culture of the university. One way to do this is to compare the engineering student sector to the other student sectors of the same university. When we compare engineering colleges at different research universities, the research universities may have different cultures that contribute to a difference in the engineering colleges. By comparing the engineering sector at Michigan to three other sectors at Michigan, it is possible to understand how engineering is different from other undergraduate programs at Michigan.

In the empirical analysis that was conducted, the model developed in Chapter II was adhered to. As discussed in the introduction to this chapter, eight hypotheses were developed. These are discussed each in turn.

Different Pre-College Characteristics

Hypothesis 1: A significant difference exists between the engineering sector and the other sectors in the distributions of some of the pre-college characteristics.

This hypothesis was verified. Comparison of the pre-college characteristics showed significant differences between the engineering sectors and the non-engineering sectors

(Table 7-1). Many of the significant differences were the same variables that Nicholls identified in her study of STEM and non-STEM differences (Nicholls, et al., 2007). As expected, the engineering sector had a higher math and science scores; and in their confidence in their math and computer abilities. Hours per week playing video/computer games (in high school) for engineering students was significantly higher than for the other student sectors. Despite this significance, playing video games was not a predictor of engineering student success or retention. Pre-Med students had a higher motivation for an academic career. The Non-STEM sector had higher self-rating in writing ability and a higher probability of changing a major or career.

The discriminant analysis of the engineering sector versus the non-engineering sectors showed that F11 (Confidence in Quantitative Skills), F9 (Educational Goals) and the variable "Important to make a theoretical contribution to science" were the major predictors of differences between engineering and non-engineering students. Although there were significant differences in math scores, the differences in confidence in quantitative skills were even more significant.

Academic Student Success

Hypothesis 1: The predictors for student success are different for the four sectors.

This hypothesis was verified for the first year GPA. (See Table 7-3) In addition, two sectors had significant interactions as predictors. With respect to the first year STEM GPA, the predictors were different, except F4 (Quantitative Skills) was significant for first year STEM GPA in all student sectors. (See Table 7-6) This supported the importance of the math and science preparation courses in high school for STEM courses.

The most variation was explained with the Engineering sector. The adjusted R^2 was .38 for first year GPA and the adjusted R^2 was .48 for the STEM GPA. Relative to the R^2 found in the literature with models that use pre-college characteristics, these are the best that I have seen. A special effect in modeling was made to look at interactions of the significant predictors. This contributed to the higher R^2 statistics.

For engineering students, quantitative skills are the most significant predictor of first year GPA. Engineering students also enroll in the most STEM courses. For the non-engineering sectors, students enrolled in a higher percent of social studies and other non-STEM courses. For each of the non-engineering sectors, a social engagement factor was found to be significant. This is consistent with Tinto's theory of college retention (Tinto, 1993). The fact that the engineering sector shows no significant predictor related to social engagement and the non-engineering sectors show a significant predictor related to social engagement strongly support the thesis that a model for student success is different for the engineering sector. While the non-engineering sectors followed Tinto's model with a significant social engagement factor, the Engineering sector did not.

Hypothesis 2: F4 (Quantitative Skills) will be a significant predictor for student success.

This hypothesis was verified for the first year GPA, Engineering sector only, and for the first year STEM GPA, all sectors. A major difference between the engineering sector and the non-engineering sectors was that while quantitative skills were very significant for student success as measured by the **first year GPA**, they were not significant for the non-engineering sectors. Since academic probation was based on the overall GPA, it is important to understand this difference between engineering and non-engineering majors.

Most students take some STEM courses (science, technology, engineering or math) and the analysis concluded that quantitative skills were important for performing academically well in these courses for all sectors.

Hypothesis 3: There will be differences in both the overall GPA and STEM GPA across student sectors.

This hypothesis was verified that there was a difference for overall GPA but not for the STEM GPA. On the average, the overall GPA for the engineering sector was less than for the other student sectors. The distributions of STEM GPA were similar across student sectors. The percent of students with an overall GPA < 2.5 was 15% for engineering students compared to half this percent (5-8%) for non-engineering student sectors.

Comparison of the overall GPA with the STEM GPA showed that the engineering sector had the same GPA of 15% (Table 7-15). This is probably attributable to engineering students take a large number of STEM courses.

Table 7-15: Percent of Students with a GPA < 2.5 for the Overall and STEM GPA for All Students and Calculus I Students

Percent of Students With GPA < 2.5	All Students (Figure 7-3)	Calculus I Students Only (Figure 7-15)
Overall First Year GPA		
Engineering	15%	18%
Non-Engineering	5-8%	4-13%
STEM GPA		
Engineering	15%	23%
Non-Engineering	28-37%	14-27%

Only 5-8% of the students in the non-Engineering sectors earn an overall GPA < 2.5, compared to 15% of the engineering students. To understand this better, the subset of students whose first math course is Calculus I was considered. The GPA and STEM GPA showed the same relative patterns for the Calculus I students. (See Table 7-15). The Calculus I non-Engineering sectors had a lower percent of students with a first year GPA < 2.5 than the Engineering students. In addition, using the Kruskal-Wallis test, there was no significant difference between the sectors for the Calculus I students for the STEM GPA, while there was a significant difference for the distribution of overall GPA.

Thus it appears that the STEM courses have a different grading scale(more low grades) than the non-STEM courses. Since engineering students take the most STEM courses of the four sectors, they are more likely to have a lower overall GPA than the other sectors.

Hypothesis 4: Differences in first year GPA by gender and ethnicity will be explained by academic preparation levels.

This hypothesis was verified. Once the first year GPA by gender or ethnicity was adjusted for the significant covariates in the model, there was no significant difference in gender or ethnicity. This was also true for the first year STEM GPA.

Retention

Hypothesis 1: University Retention for the engineering sector will be related to the first year GPA and math preparation. Other factors will influence retention for the non-engineering sectors.

Because of the small sample size in the group of engineering students who left engineering, the logistic regression prediction of university retention was limited to two predictors. Neither one was math preparation. For the engineering sector, the significant predictors were high school rank and concern about finances (for college). For the non-engineering sectors, the first year GPA was the only significant variable. Sector was found to be significant in a logistic regression model of university retention.

Female students for all sectors appear to factor in their retention decision based on their college GPA more than male students (Figure 7-11).

Hypothesis 2: Initial Concern about financial need and attending the student's first choice college will be a factor that influences university retention for all sectors.

Concern about financial need was a significant predictor of university retention. 78% of the students indicated in the CIRP survey that Michigan was their first choice college. Analysis consistently showed that there was no relationship between university retention and the student's first choice.

Hypothesis 3: The university retention of students who enrolled in Calculus I will vary across sectors

This Hypothesis was not verified. There was no significant difference in the university retention among sectors.

7.7.2 Recommendations

The recommendations include:

- The differences between the distributions of first year GPA and STEM GPA are striking. The difference appears to be due to the systematic different approach to grading courses. It is recommended that an engineering faculty committee review this data for further action.
- In developing an intervention program, it should be recognized that each discipline has different predictors for student success. The model for engineering student success is substantially different than that for the other sectors.
- For the STEM disciplines, F4 (Quantitative Skills) is a consistent predictor of STEM GPA for all four sectors. For any research projects on STEM courses, it is recommended as a predictor of success.
- High school rank, first year GPA and concern about finances should be considered as leading indicators for university retention.
- Although there were significant differences in the first year GPA between sectors, the retention statistics between sectors were very similar. In efforts for continuous improvement in retention, the focus should be on support systems for first year GPA.

CHAPTER VIII
CONCLUSIONS AND RECOMMENDATIONS

This thesis adds a major engineering contribution to the research supporting engineering student academic success and retention. This chapter will discuss the conclusions and recommendations based on this research.

8.1 Contributions to Improved Research Methodology

The contributions to improved research methodology are summarized by chapter.

Chapter II:

- The comparison of the research literature from two fields (engineering education and education) worked well in the development of a model. It was found that some predictors are dominant in one field and not in the other; by considering two fields, a wider net of possible predictors was created for a model. Since the model is based on empirical studies, the model can be easily applied to any university's data. This approach can be extended to other areas of research.
- Four differences between the engineering curriculum and other disciplines were hypothesized. These four differences were then used to hypothesize important concepts of a model for engineering student success.
- A model for freshman engineering success was developed. This model is based on pre-college characteristics as input and the GPA at the end of the freshman year and retention as the outputs of the model.
- The current state of continuous improvement programs by educational institutions was reviewed.

Chapter V:

- An equation for student success was developed based on the model. Dominant in the model are the first two pillars for student success, High School Academic Achievement and Quantitative Skills. This suggests a strong predictive effect of academic preparation during the high school years and the predictive effect of taking math and science courses in high school. Also predictive was confidence in quantitative skills and commitment to career and educational goals. More detail follows in Section 8.2.
- The Hotelling T^2 Technique showed multivariate stability in the data , suggesting that the multivariate techniques related to Hotelling's T^2 can be applied to education data. The Hotelling T^2 has been used effectively for improving manufacturing processes. In addition, Hotelling's T^2 may be very successful at detecting students who are in need of intervention in the first semester with a multivariate approach using pre-college characteristics.
- A set of guidelines for potential interventions consistent with the model's pillars of student success was developed. This could be used as a template by an engineering college and tailored to the college's specific programs for intervention.
- The University of Michigan has a number of intervention programs to help students. In general, it is the student's responsibility to participate in these programs. Thus, a student could participate in several programs. When evaluating an intervention program, bias could develop from students having participated in several intervention programs. In an attempt to minimize bias, the "randomized database" technique was used to choose students randomly from the database. Similar to a designed experiment, students were randomly selected from the large database to represent the combination of two levels of advising frequency and enrollment or non-enrollment in Engineering 110. In this case, advising frequency and enrollment in Engineering 110 were considered as interventions. The same technique could be expanded to more interventions.

- The factor F4 (Quantitative Skills) includes the ACT math score, the ACT science score, and the University of Michigan's math and chemistry placement scores. It was evaluated as a potential placement instrument. The technique estimated a minimal level of F4 needed as the preparation level in math and scientific reasoning for each of the freshman engineering courses. It verified the math and science entry level of several courses and indicated that two courses needed stronger preparation than is currently required for enrollment.

Chapter VI

- Prediction equations for engineering college retention and university retention were developed based on the retention model. It was found that four variables contributed to predictiveness of engineering college retention: self-rating of math ability, high school rank, concern about finances and the chance of participating in a study abroad program. For university retention, it was found that high school rank and concern about finances are predictive variables.
- The sensitivity analysis for college and university retention indicates the variation for retention, taking into account the actual range of each predictor. Within the typical (90%) range of 91 % class rank to 99% class rank, the engineering college retention varies the least, a range of 92% to 95%. From a self-rating of math ability from average to the top 10% of the student population, the engineering college retention can be expected to vary much more from 88% to 97%. For concern about finances, a major concern can generate retention of only 89% if all the other variables were controlled at the median value. (The actual engineering college retention was 94%). With knowledge of the expected range, a better idea of the risk associated with selected admission policies can be better understood. This is a significant benefit of the analysis.

Chapter VII

- The comparison of the engineering majors to other majors within the University of Michigan places the engineering student success and retention in perspective to other majors. All colleges within a university have a common culture. Studies that compare engineering to other majors within the university may exist but my research is more comprehensive than any I have seen. In this study, engineering students were compared to three other student groups: Pre-Med students, STM(Science, Technology and Math) majors and Non-STEM (humanities, social science and business) majors. Significant differences were found in predicting student success (first year GPA) among the four student groups. This suggests that a different student success strategy is needed for each group. A recommendation is made that researchers consider this in a research design of an engineering student success study.

Overall

- The research techniques used in this dissertation can be easily extended to any engineering college within a research university.

8.2 Student Success Conclusions

The conclusions from this research related to student success are summarized within the three research objectives:

Objective 1: Develop a model for freshman engineering student success and validate it with an empirical analysis

1. Using both a literature review from engineering education and education provided a broader set of pillars of pre-college characteristics for the model than just using the engineering education literature. As a result, a wider set of potential variables were considered.

2. The validation of the academic success model informs engineering education by confirming similar variables as strong predictors, compared to other freshman engineering success studies. The two strongest pillars (by percent of variation explained) in the validation by pillar and prediction by stepwise regression were P1 (High School Academic Achievement) and P2 (Quantitative Skills). This is consistent with the strength of these pillars shown in the literature review in Chapter 2. This study verified again the strength of overall strength of quantitative skills and confidence in quantitative skills. In the Besterfield-Sacre et al (1997) and Levin and Wyckoff (1988) studies, the SAT math had been significant for academic success. The Besterfield-Sacre study (1997) also had found that confidence in basic engineering skills to be a significant predictor; in this study, the self-rating of math and computer abilities were significant.

3. The empirical analysis supports a revision to the proposed model of Chapter II. The following revisions to the model for engineering student success and retention are supported:

- There is insufficient evidence to include P3 (Study Habits), P6 (Commitment to this college), and P9 (Social Engagement) in this model for Michigan. Validation by pillar for the ACT subset showed these three pillars to be non-significant.. (Table 5-1). In addition, in the stepwise regression, the factors associated with these pillars did not enter the regression for first year GPA (Table 5-2). For P9 (Social Engagement), only the variable "chance to participate in a study abroad program" entered either the academic success or retention models. Therefore, all the factors associated with P3(Study Habits) and P6(Commitment to this college) were removed from the model. In addition, all the factors and variables in P9(Social Engagement) were removed except for the variable "chance to participate in a study abroad program."
  - The relationship between Study Habits and first year GPA was very weak in this study (See Section 5.1)
  - Commitment to this college was a stronger predictor of student success and retention in the education literature than the engineering education literature. A chi-square test indicated no difference in retention between engineering students who indicated that Michigan was their first choice and those who indicated Michigan as their 2nd or more choice. Once a student starts college, it is likely that other variables are better predictors.
  - Although social engagement was a significant predictor for the non-engineering sectors, it was not a significant predictor for the engineering

sector. The one exception was the chance of participating in a study abroad program in predicting college retention. There were few significant differences among the social engagement variables between the engineering sector and other sectors. This indicates that the social engagement characteristics of engineering students are similar to that of the STEM disciplines and non-STEM majors, but that social engagement does not predict academic success as measured by the first year GPA or first year STEM GPA.

- With respect to engineering retention, the empirical analysis showed that the likelihood to participate in study abroad programs was a significant pre-college characteristic for engineering retention. Some students leave engineering with high GPAs and the best pre-college characteristic (in this study) that predicts this is likelihood to participate in study abroad programs; therefore, for this variable was added to the pre-college characteristics in the model. (See Chapter VI for more discussion)
- Due to the lack of support for social engagement, the Freshman Year Process was simplified to reflect the important of the pre-college characteristics, the first year GPA and the revised commitment to an educational goal of an engineering major.
- First year GPA was not a significant predictor for college or university retention for engineering students. Instead, the self-rating of math ability, the high school rank, concern about financing a college education, and likelihood of studying aboard during college were the significant predictors for retention within engineering; and high school rank and concern about financing a college education were significant predictors for university retention. Because the research literature supports both first year GPA and high school rank as predictors of retention, the model was changed to reflect this.

The revised model is shown in Figure 8-1.

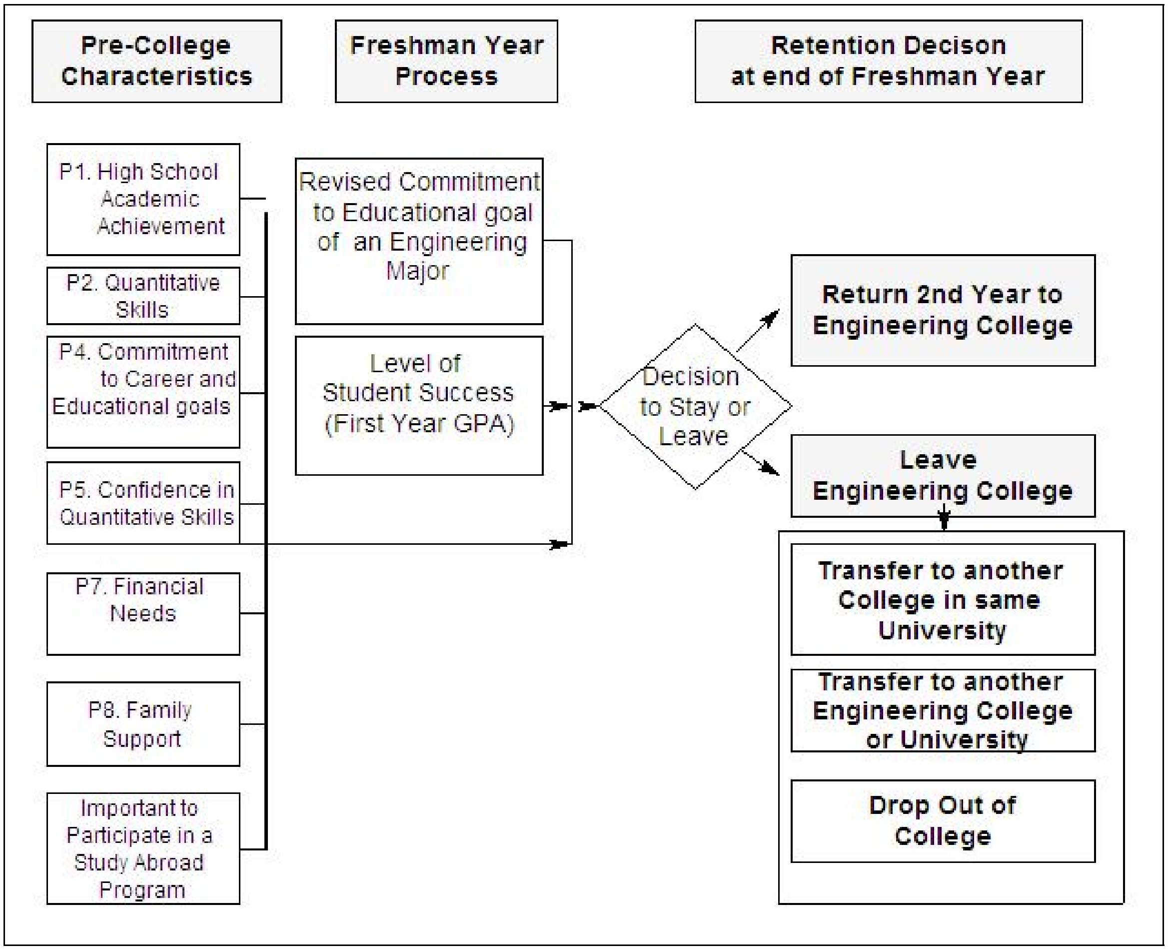

Figure 8-1 Revised Block Diagram of Model of Engineering Student Retention

The predicted equation for freshman engineering student success (GPA) is:

$$GPA = 2.921 + 0.233\ F4\ (\text{Quantitative Skills}) + .113\ F1\ (\text{High School Grades}) + 0.205\ F1xF4 + .096\ F11\ (\text{Confidence in Quantitative Skills}) -.087\ F10\ (\text{Career Goals}) \quad 8.1$$

The factors are scaled with an average of zero and approximate standard deviation of 1.0. The equations for each factor are given in Chapter V.

The predicted equation for freshman engineering (college) retention is:

$$\text{Retention} = 1/\ (1+EXP - (-6.020+ .820 \text{ x Math Ability} +.083^* \text{ High School Rank} -.717\ ^*\text{Concern about Finances} -.500\ ^*\ \text{Chance to study abroad})) \quad 8.2$$

Where Math Ability, Concern about Finances and Chance to study abroad use the same coding as in the CIRP survey (2005). Table 8-1 below shows typical values for these variables.

Table 8-1: Range of Values for Variables

Variable	Scale Range	80% Range in data
Self-Rating of Math Ability	1 to 5	3 (Average) to 5 (Top 10%)
High School Rank	Continuous	91 to 99%
Concern about Finances	1 to 3 (None, minor, major)	1 (None) to 3(Major concern)
Chance to Participate in a Study Abroad Program	1 to 4	1 (no chance) to 4 (high chance)

For example, for a student with a moderately high self-rating of math ability of 4, high school rank of 95%, major concern about finances (3) and expecting to participate in a study abroad program with a low chance(2), the predicted first year retention in engineering is:

Retention = 1/ (1+EXP – (-6.020+ .820 x Math Ability +.083* High School Rank
-.717 *Concern about Finances -.500 * Chance to study abroad))

Substituting in the values:

Retention = 1/(1+EXP – (-6.020+ .820 x 4 +.083 x 95 -.717 x 3 -.500 * 2)

Retention = 1/(1+EXP- (1.994))

Retention = .88 or 88% retention rate

Because of the major concern about finances, the predicted retention was lower than the average of 93.9%.

4. The hypothesis testing informed engineering education that once the significant predictors are statistically controlled, no significant difference in average first year GPA exists for gender or URM (ethnicity)

- There was no significant difference in the average first year GPA between male and female engineering students (Discussed in Chapter V). Admitted female students tend to have the same average F1 (High School Grades) scores as male students scores (high school rank and GPA) and significantly lower F4(Quantitative Skills) and F11(Confidence in Quantitative Skills). Because of the interaction term which is of the same magnitude as F1 (High School Grades) and F4 (Quantitative Skills), the model for first year GPA (equation 8.1) predicts a higher first year GPA than without the interaction term. As examples of predicted values of the first year GPA, consider three different scenarios for female students. The first represents the 25th percentile, the second the median and the third the 75th percentile for each predictor. Then, Table 8.1 displays the calculation of the predicted first year GPA for each of the three students.

  The model for engineering college retention includes high school rank, one of the highly loaded variables on F1 (High School Grades). As a result, once the high school rank is taken into account, there is no significant difference in retention of male and female students.

Table 8-2: Examples of Prediction of the First Year GPA for Female Engineering Students

Variable	Model Coefficient	Female 25th Percentile	Female 50th Percentile	Female 75th Percentile
Constant	2.921			
F1 High School Grades	0.113	-0.100	0.400	0.700
F4 Quantitative Skills	0.233	-0.500	0.200	0.700
F1 x F4	0.205	0.050	0.080	0.490
F11(Confidence in Quantitative Skills)	0.096	-0.200	0.500	0.600
F10 (Career Goals)	-0.087	-0.500	0.400	0.900
Predicted First Year GPA		2.828	3.042	3.243

- The average first year GPA for under-represented minority (URM) students is significantly lower than for Non-URM students. The data suggests that, on the average, URM students were admitted to engineering with significantly lower F4 (Quantitative Skills) and F1 (High School Grades) than Non-URM students. (See Table 5-7, Section 5.3.2) However, they came to engineering with a significantly higher set of engineering career goals. In a generalized linear regression, once the average first year GPA of the URM students is statistically controlled for the average level of F1 (High School Grades) and F4 (Quantitative Skills) of all students, there is no difference in the average first year GPA of URM students compared to Non-URM students. This indicates that the difference is due to the significant covariates. These covariates primarily represent unequal preparation levels. The conclusion can then be drawn that the differences in average first year GPA are due to different preparation levels, not different cultures. This is valid for the Engineering sector and across all four student sectors. As an example of predicted GPAs, Table 8.2 displays the predicted GPA for an under-represented student representing the 25 percentile, median and 75 percentile values of the predictors for engineering student academic success.

Table 8-3: Examples of Prediction of the First Year GPA for Under-Represented Engineering Students

Variable	Model Coefficient	URM 25th Percentile	URM 50th Percentile	URM 75th Percentile
Constant	2.921			
F1 High School Grades	0.113	-0.6	-0.1	0.4
F4 Quantitative Skills	0.233	-0.9	0.1	0.5
F1 x F4	0.205	0.54	-0.01	0.20
F11(Confidence in Quantitative Skills)	0.096	0.5	0.6	1.1
F10 (Career Goals)	-0.087	0.2	0.5	1.0
Predicted First Year GPA		2.785	2.949	3.142

5. This study informed engineering education that interactions are significant. For the stepwise regression for the first year GPA in the Engineering sector, the interaction F1 (High School Grades) x F4 (Quantitative Skills) was significant and contributed 6% more to the regression sums of squares. For predicting the STEM GPA in the Engineering sector (Chapter VII), two interactions were significant: F1 (High School Grades) x F4 (Quantitative Skills) and F1 (High School Grades) x F11 (Confidence in Quantitative Skills). These are the interactions of F1 High School Grades (HS GPA and rank)) with both the actual quantitative skills level and confidence in quantitative skills. This suggests that a higher level of both quantitative skills and confidence in quantitative skills compensates for a lower initial level of F1 (High School Grades) to enable student success. In both cases, the inclusion of the significant interaction term increased the adjusted R^2, an indication of a better model fit than without the interaction term. Previous studies tended to not consider an interaction effect.

Objective 2: Determine the Effectiveness of Current Intervention Strategies within the Engineering Sector at Michigan

1. **Overall, the analysis showed that engineering intervention programs improve student academic success and student retention.** What seems to be clear is that all of these intervention programs helped to retain students in engineering in the first year of college. With engineering students, the focus seemed not to be so much on engagement or involvement, as encouragement (mentoring), development of cognitive abilities, and career choice development.

2. **Mentoring supports student improvement.** Chapter V discussed the effect of a mentoring program, the advising program and Engineering 110 on student success. The improvement in the GPA of students, who were mentored, compared to those who were not, was significant. The mentored group displayed an increase of an average of 1.08 in the second semester GPA over the fall GPA.

3. **Enrollment in Engineering 110 showed significant improved retention of students both within engineering and within the university.** There was a 4.4% improvement in the engineering retention rate for students who enrolled in Engineering 110 compared to students who did not enroll in Engineering 110. There was strong evidence that enrollment in Engineering 110 coupled with a high level of advising helped some students improve their academic success.

Objective 3: Significant Differences between the Engineering Sector and the Non-Engineering Sectors

1. **This study significantly informed engineering education on the relationship between engineering and the three non-engineering sectors (Pre-Med, STM and Non-STEM).** Throughout this research, there were significant differences between the engineering sector and non-engineering sectors. The differences were more evident with the modeling of student success and much less evident for modeling retention.

- Some of the predictors for student success (GPA) for the Engineering sector were in different pillars of student success than for the non-engineering sectors.
- The generalized linear model showed a significant difference in the first year GPA, between the sectors, even after the first year GPA was adjusted for the covariates in the model .
- All the student sectors included the F4 (Quantitative Skills) as a significant predictor of first year STEM GPA. The other predictors for STEM GPA were different for each sector.
- The Engineering sector showed the highest adjusted R^2 using the pre-college characteristics included in the model for the first year GPA and STEM GPA. This suggested that the set of pre-college characteristics were better predictors for the Engineering sector than for other student sectors.
- For university retention, for the Engineering sector , both the first year GPA and high school rank were predictors of retention, with the high school rank combined with concern about finances providing a stronger prediction than the first year GPA. On the other hand, NO pre-college characteristics were significant predictors for the Non-STEM sector. It is a significant finding that no pre-college characteristics were significant and warrants further research. This finding supported that Engineering retention is different from the Non-STEM sector and that the Engineering retention is more predictive by some pre-college characteristics (i.e. high school rank and concern about finances). whereas the retention of the Non-STEM sector is not predictive by the pre-college characteristics. The first year GPA was a significant predictor of retention for the Pre-Med and STM sectors, consistent with the model.

2. **The Differences between Engineering and the STM disciplines informed engineering education.** Typically, the STEM disciplines include engineering students. In this research design, engineering and pre-med students were in separate

student sectors from the rest of the STEM disciplines. In this research, the predictors of student academic success for the STM sector (STEM disciplines without the Engineering or Pre-Med sectors) were more like the Non-STEM student sector than the Engineering Sector. F4 (Quantitative Skills) and F11 (Confidence in Quantitative Skills), which were significant predictors for first year GPA for the Engineering sector, were not significant for the STM sector. Instead, F2 (High School Performance), F7 (Study Habits-homework), F17 (Social Engagement-Socializing) and F15(Financial Needs) were significant. The modeling of the STEM GPA showed a difference in predictors also. For the Engineering sector, F10 (Career Goals) and F11 (Confidence in Quantitative Skills) were significant predictors and not for the STM sector; F2 (High School Performance) and F15 (Financial Needs) were significant for the STM sector and not for the Engineering sector. This suggests more separation in key predictors that affect student academic success between the Engineering sector and STM sector than previously thought.

3. Variation in Grading as a Engineering Retention Issue

It seems very probable from the data presented in Chapter VII that the STEM courses were graded on a higher standard scale (more low grades) than non-STEM courses. At the same time, the model predicted that engineering students who entered engineering less prepared in quantitative skills were then more at risk of academic probation (GPA < 2.000). The data supported that the engineering sector had a lower average GPA than the non-engineering sectors. A lower average GPA is consistent with the Astins' multi-institutional study of 1985-1989 (Astin and Astin, 1992). More evidence of inequity in grading was present with students who take Calculus I. Engineering students who began in Calculus I did not have a statistically significant different distribution for the ACT Math score (indication of preparation) or for the STEM GPA than the other sectors; however, there was a significant difference (lower) in the distribution of first year GPA for Engineering students compared to Non-STEM students. This again appeared to be due to inconsistent grading standards between the STEM courses and non-STEM courses.

Nationally, there is a high awareness of the need for more engineers and scientists (NAS, 2005). The National Science Board has recently expressed their concern about the shortage of scientists and engineers (NSB, 2007). Adelman's path model suggested that if one path is exceedingly difficult, the student will choose one of the competing paths, which are just as desirable (Adelman, 1998). For example, if a student was achieving low grades in engineering, he/she may transfer to another major (such as business) that was considered just as rewarding. With different grading systems within the same university, if grading of engineering courses is tougher, then applying Adelman's model, engineering may unnecessarily lose potentially competent engineers to other majors.

The University of Michigan has a significant mission of increasing its representation of under-represented minority students. Research has shown that increased representation of minorities increases the depth of thinking that is important for active learning and intellectual engagement in a college education and a successful career. (Gurin, et al., 2002) As a result, during the time of this study, Michigan gave preferential treatment to some minorities and female engineering students. In November 2006, voters approved Proposal 2 to amend the Michigan constitution "to ban public institutions from discriminating against or giving preferential treatment to groups or individuals based n their race, gender, color, ethnicity or national origin." (University of Michigan, 2007) In the future, it may be another group of students, who provide diversity to the university. Students who provide diversity to the university and come from high schools with fewer college preparation and AP courses but, yet are generally well-prepared for college, will struggle within a university with a competitive grading system. In addition, the Watson and Froyd (2007) model for increasing diversity in engineering suggests that in the transition of high school to engineering college, three areas of development take place:

- cognitive development
- identity development
- career choice development

If there is great difficulty in one area, personal energy is taken away from the overall rate of learning in college. These ideas support a less competitive environment in the freshman year of engineering.

This variation in grading between the Engineering sector and Non-STEM sector warrants further discussion within the university.

4. Hypothesized Differences Verified

In Chapter II, it was hypothesized, that there were four differences that affect freshman-engineering success when compared to other disciplines. These are discussed below.

1.) **A major in engineering prepares for a specific career, similar to other pre-professional and professional programs**.

In the multiple comparison analysis (Chapter VII, Table 7-1), it was found, that for the question concerning the importance of going to college to get training for a specific career and the questions concerning career or major change, that there was no difference in the average for engineering compared to Pre-Med or the STEM disciplines, but there was a significant difference between Engineering and the Non-STEM disciplines. This finding confirmed that the STEM disciplines (including Engineering) were more focused on a specific career than the Non-STEM disciplines and confirmed this hypothesis.

These survey questions were present in the P4 pillar, Commitment to Career and Educational Goals. This is supportive of the supposition that P4 Commitment to Career and Educational Goals would be supported in the model for engineering student success.

2.) **The engineering student is preparing for a career an as analytical thinker.**

Therefore, the freshman curriculum is the most intense in the math and science courses. The STEM GPA analysis (Chapter VII) showed that the Engineering sector students took the most STEM courses and had the highest average STEM GPA of all the student sectors. This hypothesis is confirmed. In addition, F4 Quantitative Skills, the factor for P2 Quantitative Skills was significant as a predictor of first year GPA only for the engineering sector. This finding is supportive of the supposition that Pillar P2 Quantitative Skills would define this difference between engineering and other disciplines.

3.) **Expectations for admissions to an engineering program include a wide range of college-prep courses with a large number of math and science courses.**

In the multiple comparisons analysis (Chapter VII), it was found that the Engineering sector had a significantly higher average than each of the other sectors did for the ACT Math, ACT Science, U-M Math Placement test and the U-M Chemistry Placement test. This hypothesis was confirmed. These are variables in F4 Quantitative Skills , which defines the P2 pillar, Quantitative Skills. This difference is, therefore, supported in the model.

4.) **The freshman engineering curriculum tends to be very competitive. Those students who have the stronger pre-college preparation in math and science will have an advantage.**

As has been discussed in Chapter VII, there is evidence of a different grading scale for the STEM courses than for the Non-STEM courses. The model prediction and the results in Chapter VII clearly showed that the higher standards for grading for the STEM courses disadvantages the less prepared engineering students because of the high number of STEM courses that they take. The academically well-prepared students demonstrate high grades, consistent with the model. This hypothesis is considered to be confirmed. Consistency of support across all pillars was not present. The most support was for P1 High School Academic Achievement and P2 Quantitative Skills, which are directly related to overall academic preparation and preparation in the analytical skills.

All four hypotheses were confirmed for the differences between the freshman-engineering curriculum and other freshman programs.

Overall

Michigan Engineering has a high freshman retention rate both because of the quality of the preparation of admitted students and because of the its interventions programs

One of the reasons given for conducting a single institution study at the University of Michigan was to research the modeling of student success at an engineering college with a high success rate. It has been shown in this research, that the freshman engineering retention rate was 93.9%. for the 2004-2005 cohorts. The prediction equation supported the importance of academic preparation for academic success in the first year of engineering. The median high school rank of the combined 2004-2005 cohort sample was 96% with 90 percent of the students having a high school rank of 91 percent or higher. The average ACT Math score for engineering students was 30.6; the average ACT Science score was 29.4; and the average U-M Math placement test score was 20.7. All of this indicates a very selective admissions process that generated an academically-oriented freshman class.

Consistent with the model (equation 8.1), this high level of academic preparedness contributed to the academic success. In addition, high school rank was found to be a significant contributor to freshman retention. Thus the high level of academic preparedness as indicated by the high school rank also explains the high freshman retention rate. Other variables that contributed to a high retention rate was a high degree of confidence in math and computer abilities and a low percent of students who had major concern about financing college. For students who struggle academically, the evidence provided in this research indicates that mentoring and advising support student success. In addition, the retention of students who enrolled in Engineering 110 was found to be 4.4% higher than for students who did not enroll in Engineering 110. In summary, it is a combination of high academic preparedness, a low level of concern about finances and student support programs that led to the high freshman retention rate.

8.3 Recommendations

The following is a discussion of recommended systematic and process improvements for engineering academic success and retention. These recommendations are both for the engineering education community, in general, and the University of Michigan, in particular.

1) Academic Integration is More Important than Social Integration for Engineering Academic Success.

This research adds to previous research that supports the importance of academic integration for engineering students; more so than social integration. The Pareto chart in Figure 8-2 indicates that P1 (High School Academic Achievement) and P2(Quantitative Skills) are the first two significant predictors for student success and Social Engagement factor has a low contribution. Both P1 (High School Academic Achievement) and P2(Quantitative Skills) are oriented towards academic characteristics.

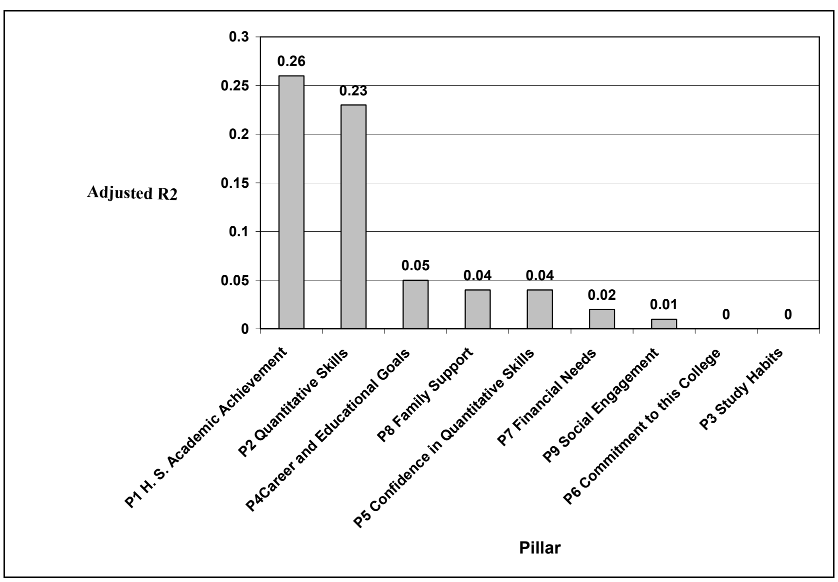

Figure 8-2: Pareto Chart of Adjusted R^2 by Pillar for the ACT Subset

In addition, in the stepwise regression prediction of the first year GPA for engineering students, F1 (High School Grades) and F4 (Quantitative Skills) were the two most significant factors, contributing 30% of the explained variation in the first year GPA. The high school GPA and high school class rank were loaded on F1 (High School Grades). F4 (Quantitative Skills) included the ACT math score, the ACT science score, the U-M math placement test score and the U-M chemistry placement test score.

The freshman engineering academic curriculum for all engineering colleges focused on the STEM courses. Thus, the modeling of the first year STEM GPA in this single institution study was relevant to student success concerns of all engineering colleges. The modeling of STEM GPA showed that F4 (Quantitative Skills), one of the academic preparation factors, was the most significant predictor for engineering students and for ALL of the student sectors. A possible limitation of this study in applying the results to other universities is that F4 (Quantitative Skills) included the U-M placement test scores (specific to the University of Michigan). Yet, the significance of F4 (Quantitative Skills) is consistent with other studies. Previous studies, including the Astin and Astin (1992) study, showed the SAT Math to be significant. Adelman (1992) found that "the highest level of mathematics one studies in secondary school has the strongest continuing influence on the bachelor's degree completion."

In addition, the literature review in Chapter II showed consistently wide support for the High School GPA and High School Class Rank as predictors of the college GPA. These two variables are included in F1 (High School Grades).

With this evidence of the importance of academic preparation, student support needs to be focused on academic support, in terms of tutoring programs and curriculum design. In addition, engineering students are most at risk of the four student sectors studies for low grades, with the lowest average first year GPA. Since engineering has the highest percent of students (15%) with a first year GPA less than 2.5 (of the four sectors), more aggressive programs to help engineering students in the first year with academic success in the STEM courses is needed than for the other sectors. Prediction equation 8.1 indicates the importance of F1 (High School Grades) and F4 (Quantitative Skills) for engineering programs. On the average, academically well-prepared students will earn a high first year GPA. However, students who are not well prepared will tend to earn a substantially lower GPA. Preparation, in accordance with the model, is more important than motivation.

In addition, this study supported having student programs that support building students' confidence in quantitative skills. This could be included in the design of the freshman STEM courses.

2) Career Development Courses are Important for Freshman Engineering Success

The recommendation is to expand Engineering 110, the engineering survey course, to a larger enrollment. Significant success in retention was evident. More programs like this are needed at all engineering colleges., The evidence is clear that one reason the College of Engineering has a very high retention rate is due to enrollment in Engineering 110. Without it, the retention would be 1.5% lower (taking into account that only one-third of the students in the study's cohorts were enrolled in it. This research indicates targeted enrollment of certain groups of the student population may be appropriate. More confirmatory research in this area is recommended.

I found no research papers in the literature on the effectiveness of engineering career courses. At a national level, this type of course needs be discussed and researched in more detail. At Michigan, an increase in enrollment is recommended. In addition, it may be appropriate to consider a career course for each discipline (especially the STEM disciplines).

3) Extend this study's interventions to other current interventions. As has been discussed in this research, each university and especially public universities have limited funds. What we would really like to know is which interventions (or combination of interventions) have the most effect on engineering student academic success and retention. For example, in this research, it was shown that a high level of advising and enrollment in Engineering 110 improves academic success of engineering students. Other programs like tutoring and mentoring could be studied within the context of the model. They were not studied in this research because of limited documented data. Connecting the cost of each program with the benefit in terms of student success is the next step.

4) Further study of the Pre-Med and STM Student Sectors. As discussed in Chapter VII, there were significantly different predictors for student academic success for these two sectors than for the Engineering Student Sector. If there is interest in the Michigan research community for understanding the freshman year and what contributes to student success for these two sectors, the research could be extended using the current database.

5) Extend this research to other universities. This research was limited to the University of Michigan. Because it was a single-institution study, it has limited extension to other universities. The next step would be to validate this model at several peer universities. As with this study, the effect of the interventions on student academic success and retention could be evaluated, controlling for the significant pre-college characteristics. It is recommended that the results from this study can best be applied to other research universities with approximately the same admissions criteria, a freshman retention rate >92% and similar graduation rates (75-85% 6-year graduation rate).

6) Consideration of a Broader set of Variables for Placement into STEM courses
Correct placement into the first term courses in an engineering college is tremendously important for a continuous improvement strategy in student success (Budny, 1998). The use of F4 (Quantitative Skills), as a placement indicator, was very successful and should be evaluated in future research. F4 includes the ACT math and ACT science scores and the two University of Michigan placement test scores (math and chemistry) combined into one factor (from a factor analysis). By the time a student matriculates into the freshman class, the ACT or SAT scores are a year old. Combining them with the placement test scores taken during freshman orientation gives a balanced perspective of the student's analytical skills. The preliminary results from this research indicate that Physics 140 and Engineering 101 should require a prerequisite of completion of Calculus II (Math 116). Other engineering colleges could explore an approach similar to this one.

Correct placement can also be important with AP students (students who are placed into higher-level math courses because of the AP Calculus tests). In particular, at the University of Michigan, it is recommended that the placement of students who earn a 4 on the AP Calculus AB test should be reconsidered. The analysis in Chapter V supports the need for a different section of Calculus II for engineering students who earned a "4" o the AP Calculus AB test.

7) A stronger use of the ACT variables is recommended. The ACT variables were considered in this analysis because of the success of using them in previous research. Furthermore, in the state of Michigan, the ACT test is replacing the Michigan Educational Assessment Program test for high school proficiency; all high school students will be required to take the ACT test. (Michigan Department of Education, 2007). Other states may adopt the same policy. Thus for the University of Michigan, it can be expected that more students will report the ACT test for admissions.

The ACT Math score tests for competence in trigonometry and some pre-calculus; the SAT Math score test only through Algebra II. (See Veenstra and Herrin, 2006a, for more detail). Because readiness for calculus is important for academic success in engineering, the ACT Math test is a potentially stronger predictor than the SAT Math test. Almost all the engineering education literature research shows the use of the SAT Math exclusively as a predictor of student success. In some cases, this has been because some universities only accept the SAT test for admissions. The predictiveness from the ACT and SAT test score subsets were very similar in this research, with the ACT Math explaining 23 percent of the total variation in the first year GPA. In the stepwise regressions in Sections 5.2.2 (Table 5-4), the ACT subset showed an adjusted R^2 of .38 compared to the SAT subset with an adjusted R^2 of .37. Thus, it is recommended that the ACT Math score should be more universally considered as a viable pre-college predictor for engineering academic success in retention studies.

8) Significance of the CIRP variable that it is "important to participate in a study abroad program" needs to be further investigated as a predictor of retention. There are two issues here. Most engineering freshmen do not plan to participate in a study abroad semester. Traditionally this has been an option in liberal arts programs. However, in recent years, as indicated in *The Engineer of 2020* (NAE, 2004), having experience in the international engineering environment is part of an engineer's proposed education. The second issue is that female students who indicated that it was important to participate in a study abroad semester had a lower retention rate. It is recommended that it be reviewed if freshmen are adequately informed of the opportunities in studying abroad. This may be a variable that indicates another retention issue (such as inherent career choice), unrelated to studying abroad. More research is needed to understand this data better.

9) The sensitivity analysis of college and university retention of engineering students clearly shows that the retention could be substantially lower than it is. Currently the engineering college retention is 93.9%. The sensitivity analysis projects a range of 86% to 97.6% for engineering college retention. For the university retention of engineering students, the retention was 97.6% with a range of 93 to 100%. This sensitivity analysis can be used to plan for future student populations. For students at-risk, equation 8.2 can be used to predict the expected retention of the students. High school rank, first year GPA and concern about finances are considered as the leading indicators for university retention.

The University of Michigan and Michigan Engineering have a history of making successful transformations (Duderstadt, 2007). Duderstadt wrote of the Vision of 2017, (a futuring project for where the university would like to be in 2017), "It sought to build the capacity, the energy, the excitement, and the risk-taking culture necessary for the university to explore entirely new paradigms of teaching, research, and service". If we are to take the national crisis of the shortage of engineering students seriously, we must consider changing the culture to continuously improve the way we support students and do it with data-based decisions. Some of these programs are relatively easy, i.e. more advisors or tutors, but some are more systematic. Tinto indicates that the classroom is where academic integration must begin (Tinto, 2006). In some cases, the paradigms of learning and teaching must be changed. An example of the new paradigm that is needed is the teaching of Engineering 110. It gives connectedness of freshman engineers to the top faculty in the College in a classroom; at the same it provides the bridge between high school dreams and a career as an engineering as a reality. In this transformation, more integrated programs like Engineering 110 are needed. In addition, I would like to recommend a data-driven culture to "engineer" student success.

Looking to the future, I would like to encourage more engineering researchers to conduct similar research to expand the engineering education community's understanding of the processes that work for engineering student success.

APPENDICES

APPENDIX A

Means and Standard Deviations of Variables by Pillar

Table A-1: Table of Averages and Standard Deviations For the 2004 and 2005 Cohorts

Note: This table represents the statistics of the students included in the comparisons by student sectors.

Variable	2004 Cohort			2005 Cohort		
	N	Average	Std. Dev.	N	Average	Std. Dev.
P1. High School Academic Achievement						
1. High School GPA	1459	3.76	.26	1783	3.76	.27
2. High School Class Rank	1458	95.56	4.81	1781	95.56	5.59
3. ACT Composite	1143	28.74	3.04	1396	28.88	2.95
4. SAT Composite	947	1301.12	126.71	1090	1314.12	125.84
5. Self-Rating of Academic Ability	1470	4.37	.58	1786	4.34	.59
6. Self-Rating of Cooperativeness	1468	3.96	.74	1785	4.01	.71
7. Self-Rating of Leadership Ability	1467	3.89	.85	1788	3.92	.82
8. Self-Rating of Writing Ability	1466	3.71	.83	1784	3.68	.83
9.Self-Rating of self-confidence (intellectual)	1468	3.94	.77	1784	3.95	.75
P2. Quantitative Skills						
1. ACT Math Score	1151	28.69	3.80	1431	28.82	3.76
2. SAT Math Score	947	666.05	75.94	1090	674.72	74.38
3. ACT Science Score	1151	27.47	3.93	1431	27.62	3.94
4. UM Math Placement	1443	17.35	5.81	1752	18.19	5.59
5. UM Chemistry Placement	1200	20.96	7.38	1371	21.60	7.28
P3. Study Habits						
1. Hours per week in the past year spent on studying/ doing homework	1457	4.83	1.50	1763	4.80	1.49
2. Hours per week in the past year spent talking to teacher outside of class	1456	2.60	.96	1756	2.55	.90
3. Hours per week in the past year spent reading for pleasure	1445	2.95	1.27	1739	2.93	1.26

Variable	2004 Cohort			2005 Cohort		
	N	Average	Std. Dev.	N	Average	Std. Dev.
P3. Study Habits (continued)						
4. Frequency of using the Internet for research or homework	1473	2.85	.36	1789	2.86	.35
5. Frequency of studying with other students	1471	2.33	.60	1792	2.29	.60
6. Frequency of asking a teacher for advice after class	1472	2.13	.61	1788	2.11	.60
7. Frequency of tutoring another student	1467	1.97	.67	1784	1.94	.69
8. Frequency of coming late to class	1469	1.77	.62	1775	1.77	.61
9. Frequency of feeling overwhelmed by all a student had to do	1470	2.11	.60	1788	2.12	.58
10 Importance in deciding to go to college: to learn more about things that interest me	1465	2.85	.39	1782	2.84	.39
11. Chance in the future to communicate regularly with your professors	1472	3.28	.64	1771	3.29	.61
P4. Commitment to Career and Educational Goals						
1. Highest Academic Degree that you intend to obtain (recoded)	1324	5.36	.69	1580	5.37	.69
2. Importance in deciding to go to college: to get training for specific career	1467	2.64	.59	1778	2.52	.67
3. Importance in deciding to go to college: to prepare myself for graduate or professional School	1465	2.67	.56	1775	2.66	.56
4. Importance in deciding to go to college: to be able to make more money	1465	2.56	.63	1771	2.57	.62
5. Chance in the future to change major field	1477	2.68	.81	1786	2.66	.80
6. Chance in the future to change career choice	1476	2.75	.82	1782	2.71	.82
7. Self-Rating on drive to achieve	1476	4.28	.75	1786	4.29	.718
8. Importance of making a theoretical contribution to science	1468	1.83	.92	1757	1.89	.94

Variable	2004 Cohort			2005 Cohort		
	N	Average	Std. Dev.	N	Average	Std. Dev.
P5. Confidence in Quantitative Skills						
1. Self-rating of computer Skills	1470	3.38	.79	1788	3.46	.74
2. Self-rating of mathematical ability	1469	3.91	.91	1786	3.87	.92
3. Self-rating of creativity	1468	3.66	.89	1783	3.60	.86
P6. Commitment to this College (U-M)						
1. What Choice is this college?	1477	3.62	.75	1788	3.63	.70
2. To how many other colleges other than this one did you apply for admissions?	1476	4.60	2.18	1791	4.60	2.24
3. Importance of coming to this college: college has good academic reputation	1462	2.88	.34	1776	2.90	.31
4. Importance of coming to this college: college has good reputation for social activities	1457	2.26	.70	1767	2.29	.69
5. Importance of coming to this college: Rankings in national magazine	1454	2.18	.71	1761	2.22	.72
6. Importance of coming to this college: college's graduates get good jobs	1450	2.68	.55	1755	2.72	.51
7. Importance of coming to this college: my relatives wanted me to come here	1454	1.54	.65	1764	1.56	.66
8. Importance of coming to this college: offered financial assistance	1447	1.58	.79	1760	1.59	.79
9. Importance of coming to this college: not offered aid by first choice	1432	1.17	.50	1741	1.16	.46
10. Chance in future you will be satisfied with this college	1470	3.66	.51	1773	3.69	.49
P7. Financial Needs						
1. Concern about ability to finance college education	1451	1.66	.61	1752	1.65	.61
2. How much of first year's educational expenses are expected to be from loans?	1163	2.70	1.83	1791	4.60	2.24

Variable	2004 Cohort			2005 Cohort		
	N	Average	Std. Dev.	N	Average	Std. Dev.
P8. Family Support						
1. Education Level of Father	1469	6.54	1.64	1782	6.54	1.70
2. Education Level of Mother	1468	6.13	1.62	1780	6.21	1.58
P9. Social Engagement						
1. Self-Confidence (social)	1467	3.56	.87	1785	3.61	.90
2. Hours per week in past year socializing with friends	1456	2.60	.96	1756	5.4	1.35
3. Hours per week in past year playing video/computer games	1450	2.32	1.52	1752	2.33	1.53
4. Hours per week in past year partying	1454	2.89	1.57	1753	2.82	1.56
5. Hours per week in past year working (for pay)	1454	3.62	2.41	1755	3.53	2.35
6. Hours per week in past year volunteer Work	1449	2.84	1.269	1749	2.81	1.27
7. Hours per week in past year student clubs/groups	1446	3.23	1.56	1743	3.18	1.51
8. Chance in the future you will join a social Fraternity or sorority	1474	2.16	.92	1779	2.16	.90
9. Chance in the future you will play varsity/intercollegiate athletics	1473	1.95	.96	1773	1.97	.98
10.Chance in the future you will participate in student clubs/groups	1473	3.43	.70	1773	3.48	.66
11.Chance in the future you will participate in a study abroad program	1472	2.92	.96	1778	3.02	.96
Model Output – First Year GPA	1485	3.246	.507	1799	3.249	.497

APPENDIX B

Reference List of Pillars, Factors and Variables

Table B-1: List of Pillars, Factors and Variables

Each variable is listed with its primary factor (no cross-loading).

Pillar	Factor Score	Variables Included in Factor Score
P1 High School Academic Achievement (ACT Subset)	F1 High School Grades	High School GPA High School Rank
	F2 High School Performance	ACT Composite Self-rating of academic ability
	F3 High School Leadership	Self-rating of leadership ability Self-rating of intellectual self-confidence
P1 High School Academic Achievement (SAT Subset)	F1 High School Grades	High School GPA High School Rank
	F2 High School Performance	SATI Total Self-rating of academic ability
	F3 High School Leadership	Self-rating of leadership ability Self-rating of intellectual self-confidence
P2 Quantitative Skills(ACT Subset)	F4 Quantitative Skills	ACT Math Math Placement Chemistry Placement ACT Science
P2 Quantitative Skills(SAT Subset)	F4 Quantitative Skills	SATI Math Math Placement Chemistry Placement

Table B-1: List of Pillars, Factors and Variables(continued)

P3 Study Habits	F5 Study Habits Communicate With Professors	Frequency of asking a teacher for advice after class Hours/week in past year spent talking with teachers outside class Chance in the future to communicate with professors
	F6 Study Habits Homework	Hours/week in past year on homework Frequency of student felt overwhelmed Frequency of studying with other students
	F7 Study Habits Class attendance	Came 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	Importance in decision to go to college : to prepare for Graduate/Prof School Highest academic degree aspiration
	F10 Career Goals	Importance in decision to go to college: get training for specific career Importance in decision to go to college: be able to make money
P5 Confidence in Quantitative Skills	F11 Confidence in Quantitative Skills	Self-rating of math Skills Self-rating of computer skills

Table B-1: List of Pillars, Factors and Variables (continued)

Pillar	Factor Score	Variables Included in Factor Score
P6 Commitment to this College (U-M)	F12 Goals-UM Reputation	Importance in choice of this college : Grads get good jobs Ranking in national magazines Academic reputation Social reputation
	F13 Goals-UM Choice	Choice of this institution Number of other applications to colleges
	F14 Goals-UM Financial Aid	Importance of choice of this college: My first choice did not offer financial Aid I was offered financial aid
P7 Financial Needs	F15 Financial Needs	Amount of loans for freshman year Concern about finances
P8 Family Support	F16 Family Support	Parents' education
P9 Social Engagement	F17 Social Engagement-Socializing	Hours/week in past year partying Hours/week in past year socializing with friends Chance will join a social fraternity or sorority Self-rating of social self-confidence
	F18 Social Engagement- Volunteer	Hours/week in past year in student clubs Hours/week in past year in volunteer activities
	F19 Social Engagement- Activities	Chance of studying abroad Hours/week playing video/computer games Chance will participate in student clubs

APPENDIX C:

Regression Tables for Validation of the Pillars for the ACT Subset and the SAT Subset (Table 5-1)

Table C-1: Regression Table for P1. High School Academic Achievement (ACT Subset)

Factor	Coefficient	T	P
Constant	3.019	79.08	.000
F1(High School Grades)	0.183	4.69	.000
F2(High School Performance)	0.241	6.89	.000
F3(High School Leadership)	0.011	0.30	.763
Adjusted $R^2 = 0.262$ F (3,180)= 22.62 (p=.000) N=184			

Table C-2: Regression Table for P2. Quantitative Skills (ACT Subset)

Factor	Coefficient	T	P
Constant	2.961	69.88	.000
F4 (Quantitative Skills)	0.296	7.49	.000
Adjusted $R^2 = 0.231$ F (1,182) = 56.10 (p=.000) N= 184			

Table C-3: Regression Table for P3. Study Habits (ACT Subset)

Factor	Coefficient	T	P
Constant	3.134	72.23	.000
F5(Study Habits Communicate with Professors)	-0.030	-0.77	.444
F6(Study Habits Homework)	0.013	0.32	.751
F7 (Study Habits Class Attendance)	-0.052	-1.19	.236
Adjusted R^2 = .000 F (3,180) = 0.69 (p= .562) N= 184			

Table C-4: Regression Table for P4. Commitment to Career and Educational Goals (ACT Subset)

Factor	Coefficient	T	P
Constant	3.202	73.70	.000
F8(Choice of Major and Career)	0.106	2.28	.024
F9(Educational Goals)	0.045	1.23	.222
F10(Career Goals)	-0.095	-2.14	.034
Adjusted R^2 = .048 F (3,180) = 4.11 (p=.008) N= 184			

Table C-5: Regression Table for P5. Confidence in Quantitative Skills (ACT Subset)

Factor	Coefficient	T	P
Constant	3.034	57.79	.000
F11 (Confidence in Quantitative Skills)	0.140	2.97	.003
Adjusted $R^2 = 0.041$ F (1,182) = 8.81 (p=.003) N= 184			

Table C-6: Regression Table for P6. Commitment to this College (ACT Subset)

Factor	Coefficient	T	P
Constant	3.146	72.59	.000
F12(Goals- UM Reputation	-0.060	-1.43	.155
F13 (Goals- UM Choice)	0.027	0.59	.555
F14 (Goals- UM Financial Aid)	0.003	0.08	.935
Adjusted $R^2 = 0.000$ F (3,180) = 0.81 (p=.489) N= 184			

Table C-7: Regression Table for P7. Financial Needs (ACT Subset)

Factor	Coefficient	T	P
Constant	3.139	78.79	.000
F15 (Financial Aid)	-0.088	-2.12	.035
Adjusted $R^2 = 0.019$ F (1,182) = 4.50 (p=.035) N= 184			

Table C-8: Regression Table for P8. Family Support (ACT Subset)

Factor	Coefficient	T	P
Constant	2.540	12.12	.000
F16 (Family Support)	0.137	2.91	.004
Adjusted $R^2 = 0.039$ F (1,182) = 8.44 (p=.004) N= 184			

Table C-9: Regression Table for P9. Social Engagement (ACT Subset)

Factor	Coefficient	T	P
Constant	3.121	71.93	.000
F17 (Social Engagement-Socializing)	-0.072	-1.63	.104
F18 (Social Engagement-Volunteer)	0.049	1.17	.244
F19 (Social Engagement-Activities)	-0.019	-0.48	.635
Adjusted $R^2 = 0.008$ F (3,180) = 1.47 (p=.225) N= 184			

Table C-10: Regression Table for P1. High School Academic Achievement (SAT Subset)

Factor	Coefficient	T	P
Constant	3.077	77.14	.000
F1(High School Grades)	0.236	5.64	.000
F2(High School Performance)	0.241	6.23	.000
F3(High School Leadership)	-0.022	-0.64	.527
Adjusted $R^2 = 0.295$ F (3,157)= 23.34 (p=.000) N=161			

Table C-11: Regression Table for P2. Quantitative Skills (SAT Subset)

Factor	Coefficient	T	P
Constant	3.050	66.47	.000
F4 (Quantitative Skills)	0.268	5.98	.000
Adjusted R^2 = 0.179 F (1,159) = 35.77 (p=.000) N= 161			

Table C-12: Regression Table for P3. Study Habits (SAT Subset)

Factor	Coefficient	T	P
Constant	3.167	69.03	.000
F5(Study Habits Communicate with Professors)	0.006	0.16	.876
F6(Study Habits Homework)	0.009	0.20	.840
F7 (Study Habits Class Attendance)	-0.099	-2.17	.031
Adjusted R^2 = .011 F (3,157) = 1.61 (p= .189) N= 161			

Table C-13: Regression Table for P4. Commitment to Career and Educational Goals (SAT Subset)

Factor	Coefficient	T	P
Constant	3.221	66.81	.000
F8(Choice of Major and Career)	0.054	1.04	.301
F9(Educational Goals)	0.062	1.50	.134
F10(Career Goals)	-0.070	-1.52	.130
Adjusted R^2 = .025 F (3,157) = 2.36 (p=.074) N= 161			

Table C-14: Regression Table for P5. Confidence in Quantitative Skills (SAT Subset)

Factor	Coefficient	T	P
Constant	3.081	51.45	.000
F11 (Confidence in Quantitative Skills)	0.127	2.50	.014
Adjusted R^2 = 0.032 F (1,159) = 6.23 (p=.014) N= 161			

Table C-15: Regression Table for P6. Commitment to this College (SAT Subset)

Factor	Coefficient	T	P
Constant	3.172	71.39	.000
F12(Goals- UM Reputation)	-0.095	-2.09	.039
F13 (Goals- UM Choice)	-0.000	-0.00	.999
F14 (Goals- UM Financial Aid)	0.061	1.62	.108
Adjusted R^2 = 0.023 F (3,157) = 2.24 (p=.086) N= 161			

Table C-16: Regression Table for P7. Financial Needs (SAT Subset)

Factor	Coefficient	T	P
Constant	3.177	71.46	.000
F15 (Financial Aid)	-0.051	-1.15	.252
Adjusted R^2 = 0.002 F (1,159) = 1.32 (p=.252) N= 161			

Table C-17: Regression Table for P8. Family Support (SAT Subset)

Factor	Coefficient	T	P
Constant	2.474	11.06	.000
F16 (Family Support)	0.159	3.23	.001
Adjusted $R^2 = 0.056$ F (1,159) = 10.46 (p=.001) N= 161			

Table C-18: Regression Table for P9. Social Engagement (SAT Subset)

Factor	Coefficient	T	P
Constant	3.160	65.54	.000
F17 (Social Engagement-Socializing)	-0.128	-2.74	.007
F18 (Social Engagement-Volunteer)	0.015	0.32	.752
F19 (Social Engagement-Activities)	0.000	0.00	.999
Adjusted $R^2 = 0.029$ F (3,157) = 2.61 (p=.053) N= 161			

APPENDIX D:

Regression Tables For the First Year GPA and For the First Year STEM GPA

Regression Tables for the First Year GPA

Table D-1: Stepwise Regression for First Year GPA for the Engineering Sector (ACT Subset, 2004 Cohort, N=184)

Predictor/Step	Regression Coefficient	T	P	Adjusted R^2	Final Mallow's Cp
Constant	2.921	63.70	.000		
F4 (Quantitative Skills)	0.233	6.17	.000	0.231	
F1(High School Grades x F4 (Quantitative Skills)	0.205	4.58	.000	0.331	
F1 (High School Grades)	0.113	2.92	.004	0.349	
F11(Confidence in Quantitative Skills)	0.096	2.41	.017	0.365	
F10 (Career Goals)	-0.087	- 2.37	.019	0.381	6.2

Table D-2: Stepwise Regression for First Year GPA for the Pre-Med Sector (ACT Subset, 2004 Cohort, N=100)

Predictor/Step	Regression Coefficient	T	P	Adjusted R^2	Final Mallow's Cp
Constant	3.123	65.80	.000		
F2 (High School Performance)	0.164	3.70	.000	0.098	
F1 (High School Grades)	0.152	2.28	.025	0.126	
F19(Social Engagement-Activities)	0.114	2.00	.049	0.152	2.5

Table D-3: Stepwise Regression for First Year GPA for the STM Sector (ACT Subset, 2004 Cohort, N=145)

Predictor/Step	Regression Coefficient	T	P	Adjusted R^2	Final Mallow's Cp
Constant	3.268	86.68	.000		
F2 (High School Grades)	0.176	5.03	.000	0.102	
F1 (High School Performance)	0.189	3.51	.001	0.166	
F6(Study Habits-Homework)	0.108	3.30	.001	0.210	
F17 (Social Engagement-Socializing)	0.108	2.71	.008	0.246	
F15 Financial Needs	-0.082	-2.23	.028	0.267	5.9

Table D-4: Stepwise Regression for First Year GPA for the Non-STEM Sector (ACT Subset. 2004 Cohort, N=206)

Predictor/Step	Regression Coefficient	T	P	Adjusted R^2	Final Mallow's Cp
Constant	3.319	122.42	.000		
F2(High School Performance)	0.171	6.08	.000	0.128	
F1(High School Grades)	0.106	4.41	.000	0.202	
F19(Social Engagement-Activities)	0.097	3.61	.000	0.240	
F2(High School Performance) x F19 (Social Engagement-Activities)	0.062	2.28	.024	0.255	4.1

Table D-5: Stepwise Regression for First Year GPA for the Engineering Sector (SAT Subset, 2004 Cohort, N=161)

Predictor/Step	Regression Coefficient	T	P	Adjusted R^2	Final Mallow's Cp
Constant	3.024	73.15	.000		
F4(Quantitative Skills)	0.131	2.49	.014	.179	
F1(High School Grades)	0.198	4.56	.000	.279	
F2 (High School Performance)	0.141	2.89	.004	.318	
F7 (Study Habits- Class Attendance)	-0.109	-2.98	.003	.344	
F10(Career Goals)	-0.084	-2.24	.026	.360	
Interaction of F1(High School Grades) x F4(Quantitative Skills)	0.093	2.11	.037	.374	6.6

Table D-6: Stepwise Regression for First Year GPA for the Engineering Sector (ACT Subset, 2005 Cohort, N=177)

Predictor/Step	Regression Coefficient	T	P	Adjusted R^2	Final Mallow's Cp
Constant	2.815				
F4 (Quantitative Skills)	0.439	11.62	.000	.370	
F1(High School Grades x F4 (Quantitative Skills)	0.246	6.59	.000	.493	-1.8

Table D-6: Stepwise Regression for First Year GPA for the Engineering Sector (SAT Subset, 2005 Cohort, N=150)

Predictor/Step	Regression Coefficient	T	P	Adjusted R^2	Final Mallow's Cp
Constant	2.992	59.54	.000		
F4 (Quantitative Skills)	0.331	6.56	.000	.234	
F1(High School Grades) x F4(Quantitative Skills)	0.133	2.59	.011	.316	
F15 (Financial Needs)	-0.066	-1.99	.049	.332	
F1(High School Grades)	0.095	1.91	.058*	.344	0.5

*Note: F1(High School Grades) has a p>.050. It was included due to the hierarchy rule concerning interactions, i.e. if an interaction (F1xF4) is included in a regression model, the main effects must be also.

Regression Tables for the First Year STEM GPA

Table D-7: Stepwise Regression for First Year STEM GPA for the Engineering Sector (ACT Subset, N=184)

Predictor/Step	Regression Coefficient	T	P	Adjusted R^2	Final Mallow's Cp
Constant	2.835	65.64	.000		
F4(Quantitative Skills)	0.281	7.99	.000	0.333	
F1(High School Grades) x F4(Quantitative Skills)	0.211	4.72	.000	0.400	
F10(Career Goals)	-0.112	-3.28	.001	0.423	
F11(Confidence in Quantitative Skills)	0.126	3.36	.001	0.443	
F1(High School Grades)	0.174	3.67	.000	0.466	
F1(High School Grades) x F11(Confidence in Quantitative Skills)	-0.093	-2.12	.036	0.477	1.0

Table D-8: Stepwise Regression for First Year STEM GPA for the Pre-Med Sector (ACT Subset, N=98)

Predictor/Step	Regression Coefficient	T	P	Adjusted R^2	Final Mallow's Cp
Constant	2.767	43.62	.000		
F4(Quantitative Skills)	0.286	4.50	.000	0.166	9.7

Table D-9: Stepwise Regression for First Year STEM GPA for the STM Sector (ACT Subset, N=120)

Predictor/Step	Regression Coefficient	T	P	Adjusted R^2	Final Mallow's Cp
Constant	2.834	50.99	.000		
F4(Quantitative Skills)	0.185	2.11	.037	0.211	
F1(High School Grades)	0.206	2.63	.010	0.249	
F15 (Financial Needs)	-0.124	-2.28	.025	0.276	
F2 (High School Performance)	0.174	2.24	.027	0.300	6.0

Table D-10: Stepwise Regression for First Year STEM GPA for the Non-STEM Sector(ACT Subset, N=113)

Predictor/Step	Regression Coefficient	T	P	Adjusted R^2	Final Mallow's Cp
Constant	2.909	49.01	.000		
F4(Quantitative Skills)	0.361	5.73	.000	0.233	
F1(High School Grades)	0.161	2.94	.004	0.280	
F9 (Educational Goals)	-0.155	-2.45	.016	0.311	10.1

BIBLIOGRAPHY

BIBLIOGRAPHY

ABET. (2007). Retrieved 7/25/07 from http://www.abet.org.

Academic Quality Improvement Program. (2007). Retrieved 7/25/07 from http://www.aqip.org.

ACT (2006). *ACT Policy Report: Developing the STEM Education Pipeline,* Retrieved 5/12/07 from http://www.act.org/path/policy/pdf/ACT_STEM_PolicyRpt.pdf.

Adelman, C. (1998). *Women and Men of the Engineering Path: A Model for Analyses of Undergraduate Careers,* U.S. Department of Education.

Adelman, C. (1992). *Answers in the Tool Box: Academic Intensity, Attendance Patterns, and Bachelor's Degree Attainment* [Electronic Copy] (ERIC Document Reproduction Service No. ED431363)*,* Retrieved 2/26/05 from www.eric.ed.gov.

Allen, D. (1999). Desire to finish college: An empirical link between motivation and persistence. *Research in Higher Education* 40, 461-485.

Astin, A.W., (1984). *Achieving Educational Excellence*, Jossey-Bass.

Astin, A.W. (1993, September). Engineering Outcomes. *ASEE Prism*, 27-30.

Astin, A.W. and Astin H. (1992). Undergraduate Science Education: The Impact of Different College Environments on the Educational Pipeline in the Sciences". [Electronic Version] (ERIC Document Reproduction Service No. 362404). Retrieved 2/26/05 from www.eric.ed.gov.

Astin, A.W. and Astin H. (2000). *Leadership Reconsidered: Engaging Higher Education in Social Change*[Electronic Version]*,* Kellogg Foundation

Astin, A.W. and Oseguera, L. (2005). *Degree Attainment Rates at American Colleges and Universities, Revised Edition*, HERI, UCLA.

Berger, J.B. and Milem, J.F. (1999). The Role of Student Involvement and Perceptions of Integration in a Causal Model of Student Persistence. *Research in Higher Education,* 40(6), 641-643.

Besterfield-Sacre, M., Atman, C.J., and Shuman, L.J.(1997, April). Characteristics of Freshman Engineering Students: Models for Determining Student Attrition in Engineering {Electronic Version]. *Journal of Engineering Education,* 139-149.

Besterfield-Sacre, M., Shuman, L., Wolfe, H., Scalise, A., Larpkiattaworn, S., Muogboh, O., Budny, D., Miller, R., and Olds, B. (2002). Modeling for Educational Enhancement and Assessment [Electronic Version]. *Proceedings of the 2002 ASEE Annual Conference and Exposition*, Session Number 2557.

Beyer, W.H. (1991). *Standard Probability and Statistics Tables and Formulas,* CRC Press, Inc.

Box, G.E.P., Hunter, W.G. and Hunter, J.S. (1978). *Statistics for Experimenters: An Introduction to Design, Data Analysis, and Model Building,* New York: John Wiley & Sons, Inc.

Brainard, S.G., and Carlin, L. (1998, October). A Six-year Longitudinal Study of Undergraduate Women in Engineering and Science [Electronic Version], *Journal of Engineering Education*, 369-375.

Braxton, J.M. (ed). (2000). *Reworking the Student Departure Puzzle,* Nashville: Vanderbilt University Press.

Braxton, J.M. and Hirschy, A.S. (2005). Theoretical developments in the Study of College Student Departure. In A. Seidman (Ed.), *College Student Retention: Formula for Student Success,* pp. 61-87, Westport: Praeger.

Budny, D., LeBold, W., Bjedov, G., (1998, October). Assessment of the Impact of Freshman Engineering Courses [Electronic Version]. *Journal of Engineering Education*, 405-411.

Burtner, J. (2004). Critical-to-Quality Factors Associated with Engineering Student Persistence: The Influence of Freshman Attitudes[Electronic Version]. *34th ASEE/IEEE Frontiers in Education Conference Proceedings,* Session F2E-1.

Cabrera, A.F. , Nora, A., and Castaneda, M.B . (1993). College Persistence: Structural Equation Modeling Test of an Integrated Model of Student Retention, *Journal of Higher Education,* Vol. 64.

Child, D. (2006). *The Essentials of Factor Analysis,*(3rd Ed.) , New York : Continuum International Publishing Group.

Chung, K., Koch, D., and Veenstra, C..(2005, November 21). Addendum to AMP Mentoring Program 2004-2005 Annual Report, University of Michigan, College of Engineering, retrieved May 15, 2007 from http://www.engin.umich.edu/students/amp/AMP.2004-005.Statistical.Analysis.doc.

Cokeley, S., Brynes, M.A., Markley, G., and Keely, (Eds). (2006). *Transformation to Performance Excellence,* Milwaukee: ASQ Press.

Copas, J.B., (1989). Unweighted Sum of Squares test for Proportions. *Applied Statistics,* Vol. 38(1): 71-80.

Cough, G. W. (2006). Editor's Note: Reforming Engineering Education [Electronic Version]. *The Bridge, Linking Engineering and Society*, 36 (2) Washington D.C.: National Academy of Engineering.

Cronbach, L. J. (1951, September). Coefficient Alpha and the Internal Structure of Tests. *Psychometrika,* Vol. 16(3), 297-334.

Daempfle, P.A., (2003-2004). An Analysis of the high attrition rates among first year college science, math and engineering majors. *Journal of College Student Retention*, Vol. 5(1), 37-52.

Dean, M.L., Evanecky, D.J., Hartr, N.W., Phillips, J.A. Summers, M.L., (2004). Systems Thinking: Theory Anchored in the Real World. *Proceedings of the 2004 ASEE Annual Conference and Exposition*, ASEE.

Deming, W.E, (1994). *The New Economics for Industry*, Government, Education, MIT.

Dew, J.R., and Nearing, M.M. (2004) *Continuous Quality Improvement in Higher Education.* Westport: Praeger Publishers

Dew, J., (2007, April). Quality Goes to College. *Quality Progress,* 45-52, American Society for Quality.

Dey, E.L., (2007). Strategic Perspectives on Advancing Knowledge. Presentation at the 2007 CSHPE National Conference, Ann Arbor. March 24. 2007. viewed at http://esmane.physics.lsa.umich.edu/wlap-cwis/browser.php?ResourceId=696

Donovan, R. (1984). Path analysis of a theoretical model of persistence in higher education among low-income black youth. *Research in Higher Education* 21(3), 243-259.

Duderstadt, J.J., (2007). *The View from the Helm, Leading the American University during an Era of Change.* Ann Arbor: The University of Michigan Press.

Education Trust. (2007). *College Results Online Database*, Retrieved 5/10/07 from http://www.collegeresults.org/search2a.aspx.

Elkins, R.L., and Luetkemeyer, J.F. (1974, November). Characteristics of Successful Freshmen Engineering Students, *Engineering Education,* 189-191.

Elkins, S.A. , Braxton, J.M. and James, G.W. (2000). "Tinto's Separation Stage and its Influence on First Semester College Student Persistence ",*Research in Higher Education*, Vol. 41(2), 251-268.

Elmers, M.T. and Pike, G.R. (1997). Minority and Nonminority Adjustment to college: Differences or Similarities? *Research in Higher Education.* 38(1), 77-97.

Freidman, T. L. (2006). *The World is Flat: A Brief History of the Twenty-First Century,(updated)* New York: Farrar, Straus and Giroux.

French, B.F., Immekus, J.C., and Oakes, W.C. (2003). A Structural Model of Engineering Students Success and Persistence. *Proceedings of the 33rd ASEE/IEEE Frontiers in Education Conference, Session,* T2A-19.

French, B.F., Immekus, J.C. and Oakes, W.C. (2005). An Examination of indicators of Engineering Students' Success and Persistence [Electronic Version], *Journal of Engineering Education*, October 2005, pp. 419-425.

Garson, G.D., (2006). Factor Analysis, SPSS for Windows.

Getzlaf, S.B., Sedlacek, G.M., Kearney, K.A., Blackwell, J.M. (1984). Two Types of Voluntary Undergraduate Attrition: Application of Tinto's Model [Electronic Version], *Research in Higher Education*, 20(3), 257-268.

Godfrey, B. (2002). In the beginning[Electronic Version] *Six Sigma Forum Magazine,*1(2)

Glynn, J.G., Sauer, P.L., Miller, T.E.(2005-2006).Configural Invariance of a model of Student Attrition [Electronic Version] *Journal of College Student Retention*, 7(3-4), 263-281.

Goodman, K. and Pascarella, E.T., (2006). First-Year Seminars Increase Persistence and Retention. *peerReview*, Summer 2006, 26-27

Grose, T. K. (2006, October). Trouble on the Horizon. *ASEE Prism*, 26-31.

Gurin, P., Dey E.L., Hurtado, S. and Gurin, G.(2002). Diversity and Higher Education: Theory and Impact on Educational Oucomes [Electronic Version], *Harvard Educational Review,* 72:3, 330-366.

Hartman, H. and Hartman, M. (2006, January). Leaving Engineering: Lessons from Rowan University's College of Engineering[Electronic Version] *Journal of Engineering Education*, 49- 61.

Hacker, D. (2005, November). Employment Outlook 2004-14: Occupational Employment Projections to 2014 [Electronic Version], *Monthly Labor Review*, 70-101, U.S. Bureau of Labor Statistics.

Harrell, F.E., Jr. (1999). Re: [S] Hosmer-Lemeshow Test of Goodness of Fit. *S-News Discussion Board.* April 15, 1999. wubios.wustl.edu.

Harrell, F. E., Jr., (2001). *Regression Modeling Strategies with Applications to Linear Models, Logistic Regression, and Survival Analysis.* New York: Springer-Verlag.

Harrell, F.E., Jr.. (2007). "Statistical Methods and Statistical Pitfalls in Biomarker Research", presented at the VU Biomarker Research Summit, 22 June 2007, retrieved from http://biostat.mc.vanderbilt.edu/twiki/pub/Main/FHHandouts/FHbiomarkers.pdf

Hawley, T. H., and Harris, T.A. (2005-2006). Student Characteristics Related to Persistence for First-Year Community College Students, *Journal of college Student Retention Research, Theory& Practice,* 7(1-2) , 117-142.

Hosmer, D.W. and Hjort, N.L., (2002). Goodness-of-fit processes for logistic regression: simulation results. *Statistics in Medicine.* 21:2723-2738(DOI: 10.1002/sim. 1200)

Hosmer, D.W., Hosmer, T., Le Cessie, S., and Lemeshow, S., (1997). A Comparison of Goodness-of-Fit Tests for the Logistic Regression Model. *Statistics in Medicine,* Vol 16, 965-980.

Hosmer, D. W. and Lemeshow, S., (2000) *Applied Logistic Regression,(2nd ed.),* New York: John Wiley & Sons.

Johnson, M.J., and Sheppard, S.D. (2002). Students Entering and Exiting the Engineering Pipeline-Identifying Key Decision Points and Trends. *Proceedings of 32nd ASEE/IEEE Frontiers in Education Conference*, 13-19.

Johnson, R.A. and Wichern, D.W. (1998). *Applied Multivariate Statistical Analysis,* (4th Ed.), Upper Saddle River, NJ: Prentice Hall, Inc.

Kim, J., and Mueller, C.W. (1978). *Introduction to Factor Analysis; What it is and How to Do it,* Newbury Park, CA:Sage Publications.

Koch, D.M., and Herrin, G.D. (2006). Intervention Strategy for Improving Success Rates in Calculus, *2006 ASEE Conference Proceedings* (2006-775).

Kubiak, T.M. (2005, November). Fiegenbaum on Quality: Past, Present and Future. *Quality Progress,* 57-62.

Lackey, L.W., Lackey, W.J., Grady, H.M., Davis, M.T. (2003). Efficacy of using a Single, Non-Technical Variable to Predict the Academic Success of Freshmen Engineering Students[Electronic Version], Journal of Engineering Education, Jan. 2003.

Leuwerke, W.C., Robbins, S., Sawyer, R., Howland, M. (2004). Predicting engineering Major Status from Mathematics Achievement and Interest Congruence[Electronic Version], *Journal of Career Assessment*, 12(2),135-149.

Levin, J. and Wyckoff, J. (1988, December). Effective Advising: Identifying Students Most Likely to Persist and Succeed in Engineering, *Engineering Education,* Dec. 1988, 178-182.

Lotkowski, V.A., Robbins, S.B., and Noeth, R.J. (2004). The Role of Academic and Non-Academic Factors in Improving College Retention, ACT, Inc., viewed at www.act.org/research/policy/index.html.

Matney, M.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. M. (2006). "Voting in the Streets: Students' Approach to Developing Political Identity." *What's on Our Student's Minds, 2* (2). Ann Arbor: University of Michigan Division of Student Affairs

Marques de Sá, J.P., (2003), *Applied Statistics using SPSS, STATISTICA and MATLAB,* Berlin: Springer-Verlag.

Matthews, P.G. (2004). *Design of Experiments with MINITAB,* Milwaukee: ASQ Quality Press.

Michigan Department of Education, (2007 January 26). ACT College Entrance Exams Provided By the State at No Cost to Families. Retrieved November 18, 2007. http://www.michigan.gov/mde/0,1607,7-140-5233-161099--,00,html.

Moller-Wong, C. and Eide, A. (1997, January). An Engineering Student Retention Study, *Journal of Engineering Education*, 7-15.

Munro B. H., (1981). Dropouts from Higher Education: Path Analysis of a National Sample [Electronic Version], *American Educational Research Journal,* 18(2), 133-141.

Myers, R.H. and Montgomery, D.C. (2002) *Response Surface Methodology(2nd ed.)* New York: John Wiley & Sons.

National Academy of Engineering (NAE).(2004). *The Engineer of 2020: Visions of Engineering in the New Century,* Washington DC: The National Academies Press.

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. Retrieved 05/08/07 from http://www.nap.edu/catalog/11463/html

National Center for Public Policy and Higher Education (NCPPHE). (2005). *Policy Alert: Income of U.S. Workforce Projected to Decline if Education Doesn't Improve*, Retrieved 5/14/07 from http://www.highereducation.org/reports/pa_deline/pa_decline.pdf.

National Institute of Standards and Technology (NIST). (2007). Baldrige National Quality Program, Retrieved 05/22/07 from http://www.quality.nist.gov/

National Science Board (NSB). 2004. *Science and Engineering Indicators.* Retrieved May 9, 2007 from http://www.nsf.gov/statistics/seind04/

NSB. (2006). *Science and Engineering Indicators.* Retrieved May 9, 2007 from http://www.nsf.gov/statistics/seind06/

NSB. (2007). *The Science and Engineering Workforce: Realizing America's Potential,* Retrieved 5/12/2007 from http://www.nsf.gov/nsb/documents/2003/nsb0369/start.htm

Nicholls, G.M., (2007a), communication.

Nicholls, G.M., (2007b), Defining STEM, in Ph.D. dissertation, draft copy, University of Pittsburgh

Nicholls, G.M. Wolfe, H., Besterfield-Sacre, M., Shuman, L.J., and Larpkiattaworn, S. (2007). A Method for Identifying Variables for Predicting STEM Enrollment, *Journal of Engineering Education*, 9(1), 33-44.

Oseguera, L. (2005-2006). Four and Six-Year Baccalaureate Degree completion by Institutional Characteristics and Racial/Ethnic Group. *Journal of College Student Retention,* 7(1-2), 19-59.

Padilla, M.A., Zhang, G., Anderson, T.J. and Ohland, M.W. (2005). Drawing Valid Inferences from the Nested Structure of Engineering Education Data: Application of a Hierarchical Linear Model to the SUCCEED Longitudinal Database, *Proceedings of the 2005 ASEE Annual Conference and Exposition*

Pascarella, E.T. and Chapman, D.W. (1983). A Multi-institutional, Path Analytic Validation of Tinto's Model of College Withdrawal[Electronic Version], *American Educational Research Journal* 20(1), 87-102.

Peduzzi, P.N., Concato, J., Kemper, E., Hoford, T.R. and Feinstein, A. (1996). A Simulation Study of the Number of Events per Variable in Logistic Regression Analysis. *Journal of Clinical Epidemiology,* 99, 1373-1379.

Pigeon, J. G., and Heyse, J. F., (1999). A Cautionary Note about Assessing the Fit of Logistic Regression Models. *Journal of Applied Statistics,* Vol. 26 (7), 847-853.

Pike, G.R., Schroeder, C.C. and Berry, T.R., (1997). Enhancing the Educational Impact of Residence Halls: The Relationship between Residential Learning communities and First-Year College Experiences and Persistence[Electronic Version], *Journal of College Student Development*, 38(6), 609-621

Platt, C. W., (1988). Effects of Causal Attributions for Success of First-Term College Performance: A Covariance Structure Model[Electronic Version], *Journal of Educational Psychology,* 80(4),569-578.

Pryor, J.H., Hurtado, S., Saenz, V.B., Lindholm, J.A., Korn, W.S., Mahoney, K.M. (2005). *The American Freshman National Norms for Fall 2005,* Los Angeles: University of California (HERI)

Robbins, S.B., Lauver, K., Le, H., Davis, D., Langley, R., and Carlstrom, A. (2004). Do Psychosocial and Study Skill Factors Predict College Outcomes? A Meta-Analysis [Electronic Version], *Psychological Bulletin*, 130(2), 261-288

Sadler, P.M. and Tai, R.H., (2007, July).“Transitions: The Two High-School Pillars Supporting College Science”, [Electronic Version],*Science,* 317(5837), 457-458.

Scalise, A., Besterfield-Sacre, M., Shuman, L., Wolfe, H. (2000). First Term Probation: Models for Identifying High Risk Students.[Electronic Version] *Proceedings of 30th ASEE/IEE Frontiers in Education Conference,* Session F1F.

Seymour, E. (2001). Tracking the Processes of Change in US Undergraduate Education in Science, Mathematics, Engineering, and Technology[Electronic Version] *Issues and Trends,* New York: John Wiley & Sons .

Seymour, E. and Hewitt, N.M. (1997) *Talking about Leaving: Why Undergraduates Leave the Sciences,* Boulder: Westview Press.

Shewhart, W.A. (1931). *Economic Control of Quality of Manufactured Product,* D. Van Nostrand Company, Inc., U.S.A., (republished in 1980 by American Society for Quality).

Shuman, L., Besterfield-Sacre, M., Budny, D., Larpkiattaworn, S., Muogboh, O., Provezis, S., and Wolfe, H. (2003). What Do We Know about our Entering Students and How Does It Impact Upon Performance? *Proceedings of the 2003 American Society for Engineering Education Annual Conference and Exposition, Session 3553.*

SPSS, Inc, (2006). SPSS 15.0 for Windows Software, Help Command, Stoecker, J., Pascarella, E.T., and Wolfle, L. M., (1988). Persistence in Higher Education: A 9-Year Test of a Theoretical Model[Electronic Version], *Journal of College Student Development,* 29,129-209.

Terenzini, P.T., Pascarella, E.T., Theophilides, C., and Lorang, W.G. (1985). A replication of a path analytic validation of Tinto's model of college student attrition. *Review of Higher Education* 8(4),319-340.

Tinto, V. (1993). *Leaving College: Rethinking the Causes and Cures of Student Attrition*,(*2nd ed.)* Chicago: The University of Chicago Press.

Tinto, V. (2005). Epilogue: Moving from Theory to Action, in A. Seidman (Ed.) *College Student Retention: Formula for Student Success,* Foreword*,* Westport: Praeger

Tinto, V. (2006). Research and Practice of Student Retention: What Next? *Journal of College Student Retention,* 8(1) 1-19.

Tinto, V., (2007) Rethinking the First Year of College. Retrieved at: http://soeweb.syr.edu/academics/grad/higher_education/vtinto.cfm

Tribus, M., (n.d.) "TQM in Education, The Theory and How to Put it to Work". Retrieved from http://deming.ces.clemson.edu/pub/den/theory_qinedu.pdf

U.S. Department of Education. (2006). *A Test of Leadership: Charting the Future of U.S. Higher Education.* Retrieved May 10, 2007 from http://www.ed.gov/about/bdscomm/list/hiedfuture/reports/final-report.pdf

University of Michigan, Office of the Registrar. (2006). *Freshman Retention Reports*, Retrieved 02/08/07 from http://www.umich.edu/~regoff

University of Michigan, (2007a). Student Profile. Retrieved September 9, 2007 from http://www.engin.umich.edu/about/studentprofile.html.

University of Michigan, (2007b). *Undergraduate Admissions, AP and IB Credit,* Retrieved 06/30/07 from http://www.engin.umich.edu/admissions/undergraduate/apibtransfer.html#

University of Michigan, (2007c). Proposal 2 Information,: Questions and Answers Regarding Proposal 2, Retrieved 7/23/07 from http://www.vpcomm.umich.edu/diversityresources/prop2faq.html

University of Michigan, (2007d). A Historical tour of the University of Michigan Campus, Bentley Historical Library website, Retrieved November 13, 2007 from http://bentley.umich.edu/exhibits/campus_tour/angell.php.

Veenstra, C.P, and Herrin, G.D. (2006a). Using the SAT and ACT Scores for Placement into Engineering Freshman Courses, *2006 ASEE World Conference Proceedings*, 2006-771.

Veenstra, C.P. and Herrin, G.D. (2006b). An Analysis of Graduation Rates at Research Universities, *2006 ASEE World Conference Proceedings*, 2006-760.

Watson, K. and Froyd, J. (2007, January). Diversifying the U.S. Engineering Workforce: A New Model, *Journal of Engineering Education*, 19-32.

Williamson, D.R. and Creamer, D.G., (1988). Student Attrition in 2- and 4- Year Colleges: Application of a Theoretical Model, *Journal of College Student Development*, 29, 210-217.

Xie, X-J., Pendergast, J.,and Clarke, W. (2007). Increasing the power: a practical approach to goodness-of-fit test for logistic regression models with continuous predictors. *Computational Statistics & Data Analysis,* doi:10.1016/j.csda.2007.09.027

Zhang, G. , Anderson, T.J., Ohland, M.W., Thorndyke, B.R. (2004, October) . Identifying factors Influencing Engineering Student Graduation: A Longitudinal and Cross-Institutional Study, *Journal of Engineering Education,* 313-320.

Zhang, G., Min, Y., Ohland, M., and Anderson, T. (2006). The Role of Academic Performance in Engineering Attrition, *2006 ASEE World Conference Proceedings,* 2006-1336