Development of the Academic Performance-Commitment Matrix (APCM): Understanding the Effects of Motivation and an Engineering Mathematics Curricular Intervention on Student Self-Efficacy and Success in Engineering

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DEVELOPMENT OF THE ACADEMIC PERFORMANCE-COMMITMENT MATRIX (APCM): UNDERSTANDING THE EFFECTS OF MOTIVATION AND AN ENGINEERING MATHEMATICS CURRICULAR INTERVENTION ON STUDENT SELF-EFFICACY AND SUCCESS IN ENGINEERING.

A dissertation submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

By

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ABSTRACT

Bourne, Anthony Ph.D., Engineering Ph.D. program, Wright State University, 2014
Development of the Academic Performance-Commitment Matrix (APCM):
Understanding the Effects of Motivation and an Engineering Mathematics Curricular
Intervention on Student Self-Efficacy and Success in Engineering.

The latest push to encourage workforce growth in science, technology,
engineering and math (STEM) disciplines has generated varying results. Overall,
demand for STEM graduates is outpacing the numbers available. This has motivated a
wide range of proposed solutions to increase the number of people trained to work in
these fields. While a focus on college recruitment in these areas is a necessity for
increasing numbers of STEM graduates, the expanding variety of students admitted to
university programs in STEM disciplines creates a new series of issues in higher
education. Most prominently, retention and graduation rates are low in STEM disciplines.

This study expands the understanding of the factors related to college retention,
specifically in the field of engineering, by creating the Academic Performance-
Commitment Matrix (APCM). The APCM simultaneously considers indicators related to
cognitive ability, psychosocial factors and efficacy thereby providing a more complete
profile of students. This profile, based on widely accepted measures of academic
performance, supports a more informed approach to formulating curricula and
coursework with an objective of increased retention. The APCM was developed utilizing
a carefully developed assessment tool to determine the psychosocial underpinnings of
measures of objective academic performance (MOAPs). In this study the MOAPs used
were ACT math score and GPA, both well regarded as predictors of success, however the APCM is novel in its consideration of their simultaneous impact.

By using the new APCM framework to study the success of a first-year math intervention course at Wright State University (EGR101), the impacts of the course on mathematics efficacy are readily apparent. Without the descriptive structure of the APCM, the drivers of the increases in efficacy and graduation rates are much more difficult to discern. The value of the APCM derives substantially from creating a multidimensional view of students. This study found that the outcomes of the intervention were much greater for certain student groups within the APCM framework.

The broader potential impact of EGR101 on meeting demand becomes clearer with the National Model of Engineering Education (NMEE). The NMEE incorporates the expanded understanding of the impact of EGR 101 on engineering students through the APCM in a model of engineering programs across the country. The NMEE utilizes the structure of schools by selectivity tier and provides a reasoned estimation of production of engineers through varying constraints. This is used to consider scenarios of how demand for engineers may be met through domestic production.
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1. BACKGROUND

On a personal level, obtaining a college degree is one of life’s greatest accomplishments for individuals and for their families. Many of today’s graduates are first generation college students. Becoming the first in a family to complete a college education is in many ways its own reward. Many of these students’ parents may have been factory workers or skilled labor that may have required at most a high school degree or some additional apprenticeship training, but not a four-year university degree. Modern economic trends are creating fewer of these types of careers, with a move toward a workforce requiring more classroom training. Once considered only reachable by the highest achievers and most financially gifted groups, college degrees are becoming more of a requirement for future financial and personal success.

As a source of national security and economic prosperity, the college degree, specifically degrees in technology fields, has been a part of the debate around federal budgets for decades. Evidence included in arguments for school funding models and national marketing campaigns that focus on technology degrees is that these degrees are significant to the long term economic growth of the country. Engineering and other science and technology areas are of special significance to this national debate on educational funding and programs geared toward student recruitment. Arguments for how to fund programs, how to generate new graduates and how to keep pace with the growing technological world never seem to be fully settled. Further compounding this problem is that the pace of attainment in these areas, while increasing, is not keeping up with market demand.
What must be considered, then, are the factors that actually help increase the number of students completing these degrees, and eventually the career success in technology fields and other areas of national interest. How do the government, education system, parents and students themselves increase the likelihood and positive outcomes of the pursuit in these degree fields?

1.1 Historical Data – 1950-1980

The end of World War II brought about a high level of growth in the US economy. According to the BEA (2012) from 1950 to 1954, the average annual increase in GDP was 6.6 percent, and the workforce increased by seven million workers over the same time period (BLS, 2012). This economic growth brought increased demand for an educated workforce, specifically in engineering, but the demand was not initially obvious for growing companies that had always had a steady supply of labor. Prior to this growth period, the pace of technological advancement was manageable with the workforce seemingly matching the national need. The educational institutions and pathways to careers supplied the requisite number and quality of workers necessary to sustain levels of production. Starting at approximately this time, the economy began expanding in a new way. There was an evolving demand for highly skilled workers that outpaced production of them. This was driven by an evolving spread of technology in society that had not been previously seen. This mismatch in the quality and quantity of worker demand led to a dynamic shortage. The products of tomorrow were being developed with the U.S. leading the way, yet this growth was potentially threatened by a dearth of workers (Arrow, 1959).
Supporting the effort to meet the need for new workers during this economic expansion was the creation of the GI Bill (USDVA 2012); formed as a benefit for military veterans returning from war and served to help get them trained prior to entering the workforce. This was a new opportunity for educational attainment that had not previously existed for many populations of Americans, and therefore an expansion in overall college graduates began (Census, 2012). This opportunity for education, coupled with the evolving Cold War, brought some new challenges as well. The arms race, science race and space race were beginning and the US Government made keeping up with the Soviet Union a number one priority as exemplified by the recruitment efforts of organizations like the NSA in the 1950’s (NSA, 2003).

In 1950, as an example of this focus on increasing math and science education, the creation of the National Science Foundation was legislated (NSF, 1950). This was a dramatic demonstration of the increased emphasis on science and engineering in the US and the effort to expand the exposure of students to these areas. Recruitment from these efforts provided funding, support and motivational tools to attract young people into technology fields, especially engineering. At that time, only 4% of the U.S. population had a 4 year degree. In 2009 the fraction of the population with a college degree was up to nearly 30% and has continued to climb Error! Reference source not found.) (Census, 2009). The availability of new jobs, rapidly increasing wages, and relatively untapped pools of potential workers made this initial growth possible.
Broadening the base of math and science graduates was initially relatively easy due to the low percentage of the population in college prior to this time. Increasing numbers of graduates were achieved using straightforward marketing to attract new students. New and affordable financing opportunities to pay for an education attracted students. In addition to this work, there were changes in curriculum to support growth. According to Klein (2003), the evolution of math education was a main impetus in the exposure of students to the possibility of a career in math and science from the mid-1950’s forward. As the level of curricular quality and challenge evolved throughout the 20th century, expectations for student achievement and knowledge attainment also increased. This movement, spurred partially by important political and cultural factors of
the time such as the space race, brought about an increase in the enrollment in math and science coursework among high school students.

1.2 An Evolving Dynamic

While the success in increasing college graduates in science and engineering seemed unlimited from the 1950’s through the early 1970’s, by the mid-1970’s this rate of expansion was greatly reduced. Pay in production jobs was increasing and new lucrative opportunities in banking, business and other fields began to emerge. The number of options available to those going to college increased dramatically over this period, as did the number of colleges and universities. Along with numerous other factors, these contributed to a declining number and percentage entering technology areas.

As Tax (1990) points out, fluctuations in the market for engineers began to dramatically transition in the 1980’s. Declining production of new engineers increased the competition for these workers when demand was high. To counteract the decline in the production of workers in technology fields, new marketing from government and private sectors began in an attempt to increase the pace of production of highly educated workers in technology areas and reduce the competition for attracting and retaining these workers. This resulted in a large increase in new engineers beginning in the early 1980’s. This boom in engineering graduates lasted through the mid 1980’s, but engineering enrollments dropped going into the 1990’s, leading to a dramatic decline in the number of graduates in the following years.
In the early to mid-1980’s many new engineers were needed because the older engineering workforce was beginning to retire or advancing to positions in management. This variation in demand for engineers was largely driven by workers from the first years of the Baby Boom generation. The boom and bust pattern of demand for engineers left many potential engineers with a sense of doubt in relation to their career prospects. Coupled with opportunities in other non-science fields it was understandable why many were not choosing to enter engineering.

A rebranding of the need for engineers over many years has occurred to combat a sense of unease among students about the field. This has resulted in a new round of messages from the science and engineering community approximately every ten years to communicate that there is sustained growth in these fields and that jobs are secure and satisfying. The current demand for workers in these areas is a continuing combination of growth in the role of technology in modern society as well as the effect of retiring workers.

It is estimated that over 750,000 engineers will be needed for the ten year period ending in 2022 through vacancies from retirement and new job creation (BLS 2012). It is not hard to imagine a need for this high a number considering the large generation of engineers that entered the workforce in the 1980’s. A strong and increasing demand for engineers is more stable than in other eras, creating a daunting target for numbers of engineering graduates. As in other eras, since production has not met this demand, new marketing messages are being created to help increase the student population.

The latest iteration in recent years of this branding effort established a new moniker for this area of study, Science Technology Engineering and Math (STEM). The
number of new STEM recruitment programs, the broadening of the range of efforts for existing programs and an effort to fund new programs is evident throughout academia: elementary through secondary schools; two-year community colleges to four-year universities, both public and private. The 1990’s saw the fastest growth in new technology of any decade in history and that explosive growth continues (BEA 2012). With the advent of digital technologies including cellular phones, computers and online media, the spread of technology-based products to new categories of users during this period has been as dramatic or more than any previous period in history. This has exposed most young people to science and technology early in their lives and allowed them to consider a career in a STEM field. Both the most well prepared and the lesser prepared of these potential students have been generally exposed to STEM marketing messages and specifically recruited to the best schools and programs to study in a STEM field.

In the early 2010’s there are fewer untapped reservoirs of students that meet the traditionally very high academic standard required in the STEM fields. Also the competition from other areas of education and career paths continues to draw away numbers of these traditional technology students. This has resulted in lower percentage of graduates in science and engineering fields than all but the lowest years in the 1970’s (Sevo, 2009).

Graduates in engineering fields have continually decreased as a percentage of the overall degrees awarded for nearly thirty years, despite increasing in absolute number in the most recent years (Error! Reference source not found. and Error! Reference source not found.) (NES, 2012). One possible explanation for this is the growth in the total number
of alternative degrees, lowering the percentage flowing to engineering. Alternatively, it is possible that a full saturation of the population likely to pursue degrees in engineering has been reached and that has created a ceiling of total engineering degrees that will be awarded.

Figure 2 New bachelor’s degrees in engineering v. all bachelor’s degrees

Figure 3 New bachelor’s degrees in engineering v. all STEM fields
Figure 4 Bachelor's degrees in engineering as a percent of all STEM degrees

Figure 5 Bachelor's degrees in engineering as a percent of all bachelor's degrees
1.3 Current State

The results of the continuous revamping of various marketing efforts have been mixed. Graduation numbers for engineers are increasing, but mainly driven by the overall growth in number of degrees as a whole. This increase has not kept pace with demand for engineering graduates. It seems that engineering has not increased its market share as a potential career field for young people. Stories of success include: increasing numbers of secondary schools devoted to science and math; some programs in engineering higher education have seen an influx of new students; and wages have remained high. It seems that marketing campaigns by schools and the government promising high future earnings and plentiful financial aid appear not to resonate with the most well prepared students that the technology industry desires. There is also a well-worn message that the United States has fallen behind the world in these areas (Report to the President 2012). For lesser prepared students this message may communicate that they are not capable of the academic requirements of a STEM degree.

Traditionally STEM students have top scores on standardized tests for math, such as the ACT and SAT, the two broadly accepted tests used in college admissions. Also these students have top high school grade point averages (GPA), making them desirable for a variety of college programs. The market for these top students has matured to the point of saturation by STEM fields. While there are some top level students not in STEM, it has been increasingly difficult to attract them through marketing campaigns. These uninterested students were not compelled to enter STEM by previous marketing campaigns and so it is natural that simply adjusting the marketing messages for contemporary young people again will not change their minds in large numbers.
Burke (2011) offers a critique of the intervention attempts of federal administrations, but offers few supporting ideas beyond secondary education modification and increased recruitment efforts. Because recruitments limited to top students have been ineffective historically and, because of the saturation of this market there is a relatively small marginal return on investment for the dollars spent recruiting them.

Because of this market condition, others believe that the opportunity for growing the number of STEM educated workers may only lie in the influx of workers from international populations (Stine, 2009). While it appears certain that the global economy will play a greater role in increasing worker production, the U.S. lags other growing and advanced economies in the percentage of workers completing technology-oriented degree programs. If other educational systems are able to graduate technology-oriented students at higher rates, there must be a scope to grow the number of such graduates in the US.

Interestingly, it is not always the highest achieving students that gravitate toward technology degrees. In fact, many colleges are increasing enrollments in STEM fields by recruiting beyond the highest achieving students. These colleges build enrollment with both the most well-prepared students as well as students that are traditionally considered marginal and do not meet traditional definitions of preparedness. For such universities, an important issue is that the lesser prepared students are not graduating in rates equal to their more highly prepared peers. To many, this lower rate of success is erroneously attributed to these students being incapable of completing the rigorous coursework in STEM fields. There are a few programs devoted to working with these students at the K-12 level and some in college, but results are not yet clear. Outreach programs and
nontraditional pathways are the most common development (Draeger, 2005). Additionally, the development of specialized STEM schools has been a well-received attempt at attracting new students from non-traditional pools. Many of the students that have gravitated to the STEM schools, however, fall into the group that do not have the traditional academic aptitude and preparedness that is desired in these fields. So there is a new influx of students that show interest in the field, yet are different in aptitude and academic achievement than the traditionally sought after students.

This broader population of students in engineering education requires innovative interventions and curricula that target their learning styles to improve success rates. Compared to historical engineering student populations, many of these students have a lower level of mathematical preparation and less well refined academic skill sets. These are students who have been dismissed in engineering education in previous generations. College completion in the traditional framework is a difficult task for these students. These students seem to be especially susceptible to failure in traditionally structured colleges. For these students, there is a high risk of failure in engineering programs built on a model transplanted by faculty who were trained in traditional top-tier university settings, where all students are assumed to have high levels of mathematical preparation and well refined academic skill sets.

These highly prepared students are heavily recruited and increasing numbers enrolled in engineering among these students is very expensive. All programs target these high-end students for marketing and recruitment messages, thus the competition for them is fierce and saturated. It is difficult to grow total numbers in engineering education
through marketing efforts targeted at these students when they can at best increase engineering’s market share among these students.

The colleges most likely to accept less well prepared students are nonselective in their admissions process. These schools are often innovative, striving for student success, and implementing novel programs that have not been extensively studied. For schools with nonselective admissions, the dilemma faced is to recruit less well prepared students in larger numbers than in the past and create novel educational curricula that allow them to succeed in the engineering profession based on a high educational standard.

Currently, graduation rates in engineering at nonselective schools are 20-40%. Selective schools routinely graduate at more than 80% rates overall, but only retain roughly 60% of the students that begin engineering programs in these schools (NCES 2014). Thus the number of engineering graduates can be increased through more successful retention efforts in both non-selective and selective schools. Because there is a lack of research on retention efforts for engineering programs in all schools, there is little evidence to support the notion that graduating underprepared students in the traditional college academic model is even possible. The threshold for acceptance into selective schools is generally a 27 on the math section of the ACT and a high school GPA over 3.5. These numbers vary by institution, but are a fairly average representation of the incoming student population. Non-selective schools, or open enrollment schools like Wright State, accept a much broader group of students with much lower ACT scores and GPAs (ACT 2012).
A great majority of the research on student retention rates in engineering focuses on the top-tier, highly competitive colleges and universities. The population of students in engineering at these universities is very different than at non-selective universities. So evaluation of student needs does not translate well between these populations.

Based on the available information, current conditions in the effort to increase the number of graduates in engineering are:

- Highly academically prepared students are a saturated market; most are already attending college; recruiting them to college is not necessary. It is commonly believed that most have made reasoned decisions about their career path so recruiting them to engineering from a field outside of engineering is difficult.

- Academically underprepared students are selecting engineering but they are graduating at less than half the rate of the academically prepared students. Expanded recruiting of these students is possible, but recruiting increasing numbers of students with a plan to graduate small percentages of them is an ethically flawed strategy.

- Increasing the graduation rates of underprepared students and gaining some ground in recruiting prepared students seem to be the most fruitful paths to increasing overall rates of engineering graduates.

- According to the Bureau of Labor Statistics data, the US needs to produce more than 750,000 new engineers to fill vacancies through retirement and new job creation by the year 2022.
If it is possible to increase the graduation rates of the underprepared student populations there is a potential to dramatically increase the numbers of graduates in engineering fields. Based on this an overall strategy for less-selective universities emerges: increase graduation rates on top of successful recruitment efforts. This strategy prioritizes research on replicable intervention methods that support student success in non-selective schools where graduation rates are low due to large numbers of underprepared students.

1.4 Overview

In the following chapters this dissertation describes research into better understanding the extensive factors related to success in engineering and increasing the production of engineers in the U.S. Chapter two reviews the available research outlining both the work that has been done to increase production through recruitment and the issues contributing to the need for increasing retention. Focusing on retention rather than just attraction as a method for increasing these numbers leads to greater understanding of the potential issues of lower student academic preparedness and aptitude for the target student groups. Further, the chapter covers the research into the issues related to retention and defines the parameters of the most prominent factors. These factors impacting retention include psychosocial factors and a new definition of Measures of Objective Academic Performance (MOAPs) which include innate ability (standardized test scores) and effort measures (GPA). MOAPs play a major role in defining the dynamic nature of student perceptions related to educational attainment, and support the structure of the major contributions of this dissertation as defined in Chapter 5.
Chapter three reviews a mathematics intervention program at Wright State University (EGR101) that has proven to increase retention and graduation rates of engineering students. These findings show that in its first four years, EGR101 was successful in increasing graduation rates at Wright State. EGR 101 also has a beneficial mitigation effect with respect to ACT score, reducing the dependence of graduation on ACT score. Historically, a high ACT score is a primary predictor of college success, and thus lower ACT students have been excluded in large numbers from engineering careers. Novel, fundamental relationships driving graduation rates in engineering are hypothesized base on the results in this chapter and form the foundation of the research in this dissertation. A study of student success with and without EGR 101 and relative to student demographic data shows a multi-dimensional relationship between students’ academic aptitude measured by ACT score and their effort as measured by high school GPA. This relationship motivates further study to more fully understand how these academic measures interact in a model for assessing a student and predicting success. The study of EGR 101 data using a logistic regression methodology found that EGR 101 helps all students graduate at higher rates, but has the most dramatic impact on students with low ACT scores and high GPAs. These findings motivate a need for an expanded set of research tools to study these student groups more effectively. These tools are needed to more clearly understand the reasons for this amplified success via EGR 101 in certain groups. Finally, motivated by the retention improvements demonstrated with the implementation of EGR 101, chapter three describes a novel model of student retention based on a geometric probability distribution. This model is used to demonstrate the positive impact that EGR 101 has on progress toward a degree within a revised Wright
State engineering curriculum. This model also provides a framework for assessing the potential that interventions focusing on a single course or multiple courses can have in the context of a larger curriculum.

Chapter four outlines the purpose and goals of the later chapters including developing an understanding of how EGR101 impacts students, and how these impacts may improve graduation rates. This chapter gives an overview of the goals and hypotheses of the new studies undertaken to answer these questions. These studies collected data from students in current sections of what is now referred to as EGR 1010 from August 26, 2013 to December 16, 2013 including a total of 225 students in the initial survey.

Chapter five focuses on the results of a study conducted using the Engage tool from ACT Inc. (ACT Inc. administers the ACT exam for students planning to enter college.) ACT Engage is a 108 question instrument that measures factors related to student success.

This study uncovers primary relationships driving the increased graduation rates demonstrated in EGR 101. These relationships indicate student self-concept and success are strongly related via objective measures of academic ability. The Academic
is introduced as a defining construct for describing student personality traits through the interactions of MOAPs. This research finds that MOAPS should include the measures for innate ability and motivation. From this discovery the APCM shows that these measures have statistically significant explanatory power in the study of EGR 101 and may have a more general usefulness in other areas both in education and elsewhere. The APCM redefines the perceptions of incoming students, forming four distinct student groups based on cognitive factors: Achievers, Support Seekers, Purpose Seekers and Support/Purpose Seekers. The study of EGR 101 students demonstrates that EGR 101 helps all students, but has the most dramatic impact on Support Seekers, low ACT but
highly motivated High GPA students. This multidimensional analysis is a departure from much of the educational research outlined in the literature review which primarily relies on GPA or ACT as one-dimensional measures of performance that can be assessed independently. By simultaneously utilizing two dimensions of MOAPs to analyze student perceptions this chapter develops a clearer picture of how students react to the curriculum that includes EGR 101.

Chapter six provides further evidence of the usefulness of the APCM structure through application of a new efficacy survey based on the material in EGR 101. The survey is designed to measure student’s change in efficacy from participation in an engineering math course. The results from administering this survey to a group of EGR 101 students provides further substantiation of the results from Chapter five. In particular student personality traits of efficacy (and motivation) are strongly related to the quadrants of the APCM. The survey found that the strongest impact of EGR 101 on the graduation rate of Support Seekers is mirrored by a very strong improvement in efficacy for this same group. The survey tool and approach to measuring efficacy may be further refined to provide an absolute measure of mathematics efficacy, but currently astutely measures only the change in efficacy for students taking the EGR101 course. This result of the study with this instrument strongly supports the dramatic positive effects of EGR 101 for an under-recruited group of engineering students with a statistically sound methodology.

Chapter seven introduces a system dynamics model integrating the research results from the earlier chapters into a national model of engineering education graduation rates. This model allows experimentation with potential outcomes for implementing an engineering math course similar to EGR 101 in engineering programs.
across the country. The structure of the model is based on the retention rates of students across the three college selectivity tiers. It also utilizes the APCM to distinguish current and improved graduation rates based on the success of the EGR101 intervention as supported by the research in Chapters 3 through 6. This analysis shows that the status quo curricular model with disappointing retention rates will not produce the requisite number of engineers over the next ten years under most reasonable scenarios as well as under unreasonably optimistic scenarios. For example, the model predicts that goals for engineering graduates will not be met if the annual percent increase in new enrollees in engineering triples from its current trend. This analysis demonstrates the importance of increased retention among less well prepared students as a strategy for expanding the number of engineers. The model allows experimentation with how retention increases may be realized across the APCM groups and can help guide efforts to make much greater gains in numbers of engineering graduates.
Given that the mission to increase the number of engineers in the workforce has been falling short, it is important to fully consider what has been done to both attract new students and keep students in engineering programs. As was discussed in chapter 1, the effort to recruit students into programs is a questionable strategy, but to summarily dismiss the idea that recruiting may be beneficial is ultimately not a good choice. The available research has shown that recruiting is not producing the required output, however, and other options (like retention) should be more fully reviewed as viable alternatives for the recruitment strategy if recruitment is truly not going to work. Reasons for the lack of results from recruitment may vary, but the conditions of the educational climate and the methods by which students have traditionally been chosen seem to play a role.

2.1 Attracting new talent to STEM: Are there enough traditional students to fill the pipeline?

Raiding the rolls of other STEM programs to pull in top tier students is one strategic option to grow new engineering students. Engineering colleges competing against sciences, against mathematics, against programmers; this leads to a counterproductive war for students and would have a dramatic effect on enrollment revenue for many universities, especially for the less competitive schools. It is widely assumed that students exposed to sciences will have a natural propensity for the field and so the bridge to engineering from the sciences would at least be a natural one. But again
the problem of traditionally qualified students versus underprepared students arises. Determining if there are even enough students of high qualifications available to meet demand is not a part of the recruitment strategy for individual schools. It has also been assumed that only students of a high level of aptitude for math and science will perform well in these areas and this logic is mostly founded in the current literature. This leaves many questions remaining about the viability of the recruitment option, and the reason so little has been done to consider the less qualified student.

What is troubling, however, is that the pool of the “highly-qualified” prospects is likely not expanding enough to truly increase the enrollments in engineering. The vast majority of these who have been exposed to and enjoy STEM fields, but are not in engineering, already choose a STEM career that they feel better suits them. The top level student tends to make well informed decisions, and convincing them to move away from an area of interest once they have made a decision is difficult. It would seem that the logical choice, then, would be to focus on the group of students that are perceived to be less likely to graduate with STEM degrees, but that may have come from STEM feeder schools or may not have chosen engineering in the past. Many of these students have actively sought an engineering degree, but are not graduating at very high rates.

The push for increasing graduation rates in STEM fields has led to a wide range of programs designed with that goal in mind. As has been stated, most programs related to increasing the numbers of engineers have been created to attract students of a high caliber that meet traditional measures of what will be successful in STEM curricula. Too often these programs fail to recognize that student choice, talent, and ability may come into play. Atkinson (2012) points out that generating more graduates in STEM fields is
not as easy as increasing exposure to the fields. In fact, although there was an increase in
the number of students taking math and science courses throughout the 90’s, there was a
decreasing number of students graduating with degrees in engineering over the same
period (Hennessy, 2002)

Chubin (2008) says the need for a renewed view of how to attract talent based on
generational differences is necessary. However, this study relies on the idea that
exposure leads to the decision to be an engineer, not vice versa. While this study cites
Adelman (1998) that shows a connection, it does not determine correlation v. causation.
Ultimately, the study contends that entertaining students is the best method to get them to
stay after they have selected an engineering program. The thought here is that the image
of the field must change in order to attract more students, specifically women, into the
field of engineering. This is the one area where marketing and attracting new students
may work, but has not yet shown results. The fact that women are underrepresented in
engineering shows that there is room for improvement in recruiting at least one group of
students to the field and may, therefore, efficiently serve as a way to increase graduates in
engineering. What the study also shows, however, is that the daunting nature of low
engineering retention is a turn off to new students. Until the attrition problem is solved
there may not be a way to increase the female student population numbers.

Achieving increased enrollments into engineering programs is only half the battle.
Convincing students to start down the path to becoming engineers is only a beginning and
does not guarantee they will complete the program. A student choosing to enter an
engineering major, does not guarantee they will complete a degree. The evidence
available does not represent the entirety of the educational landscape in engineering. For
example, a survey of two types of engineering schools, one private one public, but both competitive, shows that a significant percentage of those who begin an engineering major will persist. Only 20% were either unsure or not going to continue (Lichtenstein 2009). While this seems to be a fairly good reason for recruiting the same types of students that go to these schools, the numbers neglect to indicate that the cost of recruiting this type of student is high and does not speak to the issues that exist at non-selective schools. So the search for research on these types of programs and schools is important.

Pathway models may be an avenue to increase the attraction of diverse and nontraditional students early, but this still does not bring into consideration how these students will be retained. The student population targeted here is for STEM school programs, those that do not have the traditional background to be considered capable of the four year degree without interventions. This means, that despite the work to increase student interest, they are still hitting the curricular roadblock (Draeger, 2006)

2.2 Where the potential lies: What students to focus on and why

If students do not want to be a scientist or engineer because they don’t have the interest or aptitude, that is a very different scenario than if the students see barriers to completion or lack of a financial incentive. Students are at times turned off after they begin a college major in the sciences. This means that although there was some initial attraction, they eventually realized it was not for them (Seymour 1997). Perhaps removing barriers and increasing the incentives is the path toward an improvement in recruitment and eventual graduation, but it greatly depends on student interest. Sevo (2009) also shows that the range of interventions is very wide. Because student needs
vary so widely these needs that must be addressed in order to retain students. But understanding and finding solutions to these needs remains elusive.

It is also important to consider the breadth of individuals who may be interested in the STEM fields. While it is true that intellectual capability plays a role in curricular and vocational decisions, propensity of interest also asserts a force in students’ decisions. Bybee (2010) explains that STEM itself is a combination of many fields, and therefore an integrated learning model to promote its fields is necessary. This push should not be to the exclusion of student populations, but to be inclusive in its design. Let the students decide what they want to be and provide the context in which they may be successful.

To further compound this problem, or perhaps to explain it, there are extensive studies showing that underrepresented populations have greater disadvantages entering the postsecondary educational climate. As the ASHE Higher Education Report (2011) shows, the minority and underrepresented populations in STEM have substantially more deficient preparations entering college and are discouraged due to a lack of academic supports at the collegiate level. What this report shows is that, while the average college student may make decisions based on interest and have the preparation to be successful, the underrepresented groups may have the interest, but not be prepared. In the context of what Atkinson (2012) and Bybee (2010) discuss, it is vitally important to develop programming around students who are interested in and truly have the aptitude for STEM programming, but have not had the opportunity to demonstrate this aptitude through educational testing like the ACT or academic GPA.

So it is apparent that competing for a small number of highly qualified students is not a fruitful endeavor. But, can the number of students who are much less qualified in
traditional terms be helped to complete their degrees? There are many factors related to student retention in college programs and these factors have not easily been addressed adequately to date. The following sections will address the issue of factors related to retention and endeavor to narrow down the factors to a manageable, and ultimately useful, group.

### 2.3 Student Retention Factors in Broad Terms

Research on the concept of student retention issues and dropouts can be traced back to Tinto (1975) where, for the first time, student persistence was considered in a complete context. The authors worked to determine the issues preceding dropout, rather than purely looking at the dropout event as simply a snapshot in time. Until this study, it was assumed that students were very much similar and the only true issue related to persistence was academic preparation. Future research bears out that cognitive functions play a great role in the complex problem of degree completion, but there is a dearth of research showing that there are many other factors playing in concert with the academic aptitude of the student.

Elzinga (2009) and Habley (2010) provide great examples of the type of research that has been primarily done in student retention. Vast longitudinal analysis like this study provides some insight into the variety of issues college students face, and also provides structured evidence that persistence, retention and grade attainment are the key drivers of eventual success either in future courses, or in final degree award. Schmitt (2009) and Veenstra (2008) also provide studies aimed specifically at widening the breadth of data collected to determine what makes successful engineers. By utilizing
variables that include test scores and other demographics, this study works to increase the level of explainable variation in retention models. Hosch (2008) provides equally substantial support to the multifaceted approach to factor analysis. It was determined that admissions test scores were of greatest importance in predicting retention, however, GPA at the end of the 1st college semester, and living on campus were also of high value.

Future research in student retention varies greatly in approach and factor concentration. Various measurement tools have been developed over the years to analyze the effectiveness of certain factors in predicting student success. Ting (2001) utilizes the Non-Cognitive Questionnaire (NCQ) along with SAT scores to analyze the persistence of female students versus males. The Persistence in Engineering Survey (Eris, 2005) was developed with a similar purpose. This survey attempts to understand the factors related to why some students succeed while others fail; based on the understanding that standardized test scores are not the only measure of success. Lombardi (2011) utilizes a survey of academic behaviors to help define college readiness for the purpose of student retention and found that various influences were at play through the College Career Ready School Diagnostic (CCRSD). As the survey took a dramatically wide angle at readiness, the authors worked to pare down this tool to provide greater reliability as a predictive tool.

The breadth of questions in these surveys demonstrates the diverse approaches attempted to measure more than simple standardized test scores in an effort to solve the retention puzzle. In an effort to provide greater certainty with this process, Vivo (2008) provides a tool to analyze the predictive quality of retention factors in specific context.
This ROC analysis provides greater accuracy and therefore better predictive validity to these factors going forward.

The breadth of factors in these analyses is due in part to the fact that evidence has shown that test scores are limited in their predictive value even when they provide consistent results. In fact, as Currie (2012) states, only 25% of the variability in research data in relation to persistence is explained by ACT or SAT scores. The rest is, to a great degree, is unexplained.

2.3.1 ACT, IQ and Cognitive Ability

Because there has been such a focus on recruiting the best student to STEM fields, it is important to begin examining the effects of standardized test scores. Given that student’s traditionally recruited by STEM programs are those having both high ACT Math and high GPA. Despite the notion that retaining underprepared students that have an interest in the field may be the best chance at reaching graduation targets, ACT math scores remain the most dependable predictor of success in engineering programs.

Veenstra (2008) shows that standardized test scores like ACT and SAT Math scores, high school GPA and class rank are important factors in the academic success of engineering majors. This study did show a significant interaction between ACT scores and GPA, but many other studies have shown that these two factors are separable and distinct in their contribution to the prediction of college success (Currie 2012, Leuwerke 2004, Hosch 2008, Schmitt 2009, Habley 2010).

Also important is the necessity to examine STEM populations. The study by Bridges (2001) used a uniquely designed questionnaire to consider the psychological
factors related to persistence and success in comparison with GPA and SAT scores.

When reviewing the mean SAT scores of this group of introductory psychology students, it is apparent that the mean GPA and SAT scores are not representative of even the most diverse of engineering student samples. Their findings also diverge from expectation in that they found only SAT scores to be significant. The goal then, is to find studies that utilize broadly representational groups or are relevant to engineering students and engineering disciplines.

Leuwerke (2004) shows that major interest and previous achievement are important characteristics, working in concert with admissions scores to provide predictive value for retention models. This study also shows that ACT math has high predictive value for outcomes of engineering students. Kistantas (2008) does similar work with SAT, realizing that the plurality of work done in retention utilizes composite scores. This study recommends using SAT M along with self-regulation measures as a predictive factor for retention. This approach provided greater predictive value than test scores alone.

Building on our understanding of the interaction of academic scores and success, Stumpf (2002) provided a study that relates the range of ACT scores to success. By comparing 25th and 75th percentile ranges with success, they offer a model for comparison that may be extrapolated well to national data provided by the ACT organization. But the availability of this data has also lead to the systematic weeding out of potential students. Because the ACT and SAT scores are so readily available, and because of the reliability of these variables in predicting success, too often admissions decisions have been based (or even suggested by research to be based) on these factors
(Bettinger, 2011). While it is understandable that the competitive market for students has led to specific score targets, the reliance on this single predictive variable to determine the overall admissions model is an overly simplified methodology. Too often, scholarships and aid are given to students who have simply scored higher on these norm referenced exams and not given to students who, given a modicum of financial support may actually be benefited more greatly by the aid.

Fortunately there have been several studies focused on improving the value of admissions decisions predominantly based on test score data. Fouad (2010) recommends understanding the support systems necessary to supplement students of diverse backgrounds, including those with lower test scores, and also of underrepresented females in the field. This qualitative approach to identifying candidates does away with the one-size-fits-all approach that admission by score puts forward.

Currie (2012) defines factors that provide additional validity to the standardized test scores. Based on life skills areas this study was able to add an additional 9.4% to the 25% explained through test scores and high school achievement alone. While providing further support for the value of test score and GPA data, the development of life skills as an additional factor is supported by many other studies.

### 2.3.2 High School GPA and Academic Preparation

High school GPA is often utilized as a measuring stick for college preparedness and has been found to be a good predictor of college success (Allen 2010, Stumpf 2002, Schmitt, 2007, 2009). Additionally, tests of academic aptitude and mastery show similar, if not better at times, predictive value for college success (Cimetta, 2010). This is
reflected in the basis for most college admissions where utilizing standardized test scores and high school GPA are standard practice.

In practice, however, good high school grades do not always transfer to good college grades. In many ways how those grades were earned is as important as the grades themselves. Students who come by good performance without high effort are more prone to let downs in college. In contrast, students who have developed solid work ethic along with good GPAs, despite low test scores, may have a better chance at success (Komarraju, 2013).

An overreliance on standardized tests as a measure of student aptitude can also create a false impression with the student of whether they are “college material”. This perception that intelligence is a fixed parameter, and therefore learning is also fixed is a limiter for student achievement in many ways. When given the notion that they may be able to perform beyond their previous level of aptitude, many students have an increase in motivation that also increases their achievement in math courses (Blackwell, 2007). This is especially important when considering the need for increasing the number of engineers. If students feel they “aren’t math people” and never develop an understanding that they can become proficient in the discipline, low achievers may never truly commit to the idea that they can become engineers and therefore go as an untapped resource.

Further study has also shown that the number and quality of courses taken may in fact be a more significant predictor than either GPA or SAT score. Therefore, students with an interest in the field are more apt to take courses related to their potential major while in high school and may be better prepared and interested despite their general test scores (White, 1985). This provides even further support for the papers position of this research.
that recruiting students from other fields is less effective than retaining those already interested.

2.3.3 Bio Demographics, Major, School Type and Family: Diverse Systems and Limited Effects

As the search for important factors related to academic success in college widens, it is evident that factors outside academic ability and achievement must be playing a role (Ting, 1997). Just how significant each of the seemingly endless factors is depends on the context provided for each of these factors. Among the most fundamental and obvious influences in students’ lives are their families. Considering the dynamics involved in families it is interesting that more attention has not been paid to the family unit as an influence in educational attainment at the college level. Hoffman (2005) and Fife (2011) show that ACT may have a bias against minorities and therefore considered viewing college success through this lens in the absence of the potential bias. Additionally, these studies view possible alternative influences like religion and how they may affect individuals and their families. But what is difficult to measure in regards to issues like family, school environment and major, is that diversity which makes measuring differences very difficult.

Fernandez (2008) examines the experiences of first-generation college students; a demographic that is of special importance, considering that only roughly 30% of the population has a college degree. Through a qualitative analysis, the study identified many factors that affect the first-generation students through their first year of college. Having less to draw on from their parents’ experience than some of their peers, these
students have a very limited understanding of the processes associated with college. But even with this information, it is hard to pinpoint how much each individual effect has on the overall retention of these students. Perceived barriers may not rise to a challenge great enough for students to drop out, but for a minority of students, this may be the case.

In a study by Chen (2012) it was found that family support is especially valuable in stabilizing students’ GPAs throughout the year. Having social support was especially important to female students, and financial support provided stability as well. This study examined the variability in GPA scores of students and compared them to self-reported support scores. What is interesting with this study, as with most in relation to these subjective factors, is that it is the students’ perceptions of support that are being measured. It is through this first person filter that these issues are being processed and this may confound the analysis of the issue. Support may mean different things to different students (Garcia, 2012).

Given the potential variability generated from these first person accounts it is important to consider the unfiltered raw biographical data available and determine what is important (Childs, 1986). Maintaining universally defined constructs makes it easier to compare studies of similar intent. Unfortunately the literature demonstrates that many studies change the variables being studied, the method of study, or the way the questions are posed, making it difficult to compare subjective and qualitative data in this field.

In an effort to consolidate these question types and provide specificity to a degree type, Eris (2005) developed the Persistence in Engineering survey (PIE) which utilizes qualitative questions to determine the likelihood that students would remain in the field. Lichtenstein (2009) followed up this research and found that students entering the degree
field do not necessarily become engineers simply by opting into the major. They also found, importantly, that institution type plays a role in student outcomes. Schools that are more focused on technical professions had greater retention. This leads to many further questions including why students choose the type of school and degree field. The PIE has not been extensively used, however.

The decision process of students is of special interest. This choice of major and school is an important one for college recruiters and for advisors. Helping students make better decisions may also benefit persistence and degree attainment in the long run (Dahling, 2010). Determining major and college to attend is a complicated process, but support systems like family have positive influences in relation to the level of motivation students have for their degree completion (Jung, 2013). Even initial choice of school may be a mixed message. As some students choose a community college because of a lack of options, others choose these schools for practical reasons and end up transferring to a four year school to complete their degrees. Understanding these motivations can help when designing appropriate interventions for students to aid in retention (Porchea, 2010). Experience and background also play a role in decision making and these demographics tend to play a role in success of students (Vermunt, 2005). It is no surprise that the maturity of the student has a tremendous effect on the overall choice and outcome of the student. These demographics should also be considered when incorporating any interventions (Schofield, 2010).

Interventions themselves must be diverse in order to provide the best opportunity for aiding students in their pursuit of their degrees. Providing engaging instructors, peer support and mentorship all have positive impacts on students’ perception of their school
and degree as well as their ability to complete their degrees (Gasiewski 2012, Meyers 2010). There is a general lack of research determining the effectiveness of interventions.

Despite the apparent impact of family, school, major and other contextual factors, the literature does not strongly support using these effects in general models for retention. It is important to note, that they do play a role in retention, however the strong and consistent link across all student populations is simply not there. Using this information to guide interventions will serve the population, however, and the findings and future research in this area should not be abandoned altogether.

### 2.3.4 Non-cognitive Factors: Psychological Dynamics of Persistence

Where individual demographics failed to deliver consistency, the psychological factors of the individual may provide greater reliability across many groups. The field of psychology has borne out the breadth of this research, however it is important to consider the specific context of engineering students has not been exhaustively studied. The research instruments to use for these purposes have not been perfected. One such tool, the Non-Cognitive Questionnaire (NCQ), was hoped to provide solid research into the admissions process and aid this endeavor. The NCQ, while a good measure of non-cognitive variables, was found to have little validity in relation to college GPA and persistence (Thomas, 2006). But the research in the area of personality traits and retention is varied and many models have proven fruitful.

Initial review of research into the psychological and personality factors related to retention provided an overwhelming variety of studies and ways of looking at the problem. Considerable effort was invested to work through the available research to find
popular and consistent themes. In most of the studies reviewed, models included ACT, HS GPA or both in order to provide the best possible predictive value. The psychological and personality factors were then used to supplement these generally accepted measures. For instance, Gifford (2006) utilizes both ACT and GPA values adding in the concept of Locus of Control. This study considers the student’s perspective about their impact on events around them. An internal locus is one where the student feels they have the ability to influence events around them, their grades in college for example. An external locus is where the student feels these things happen to them, i.e. “my professor gave me this grade”. It was found that individuals with an internal locus had greater retention in the context of GPA and ACT scores being taken into account, than for students with an external locus. It is studies like these that make up the bulk of the relevant literature leading to this research.

Study habits in general, even as represented by work in courses outside of engineering, play a role in retention (Lackey, 2003). Even when students are assigned work without grades and without technical requirements it can be shown that the effort and skills utilized to successfully complete these assignments still have strong correlations to GPA in college. This shows that students’ innate desire to fulfill the requirements of an assignment may carry over to other areas outside their major, and is an innate function of their educational pursuits. In fact, engineering students are not that much different from other students when it comes to personality type demographics (Ohland, 2008). Commonality in this domain means that personality and habitus play an important role in how these students succeed. It is not always what motivates them, but how much they are motivated and how they respond (Gaddis, 2013).
Motivation plays a strong role in how students develop study habits and their attitudes toward work in general and has been found to be independent of intelligence measures. Work ethic can be decoupled from cognitive measures as it is been shown that high academic achievement does not necessarily require high motivation or work ethic (Steinmayr, 2009). There is a slight connection between hard work and cognitive measures, but mostly this is aligned to GPA rather than ACT scores. This forms an interesting dichotomy in how retention can be viewed and the overall effect of cognitive ability on college success (Crede, 2008). The implication of motivation, study skills and habits having a larger impact on GPA than on ACT indicates perhaps that students who are more motivated and have higher conscientiousness may have an opportunity to overcome cognitive deficiencies that produce low ACT scores.

Alarcon (2013) explored this issue of effort further and studied a wide range of potential factors related to why students drop out of college programs. They found, contrary to other studies, that parents’ levels of education were not a significant factor; this was in light of the other factors studied. The highest levels of significance were ACT score and motivation. This study viewed students’ conscientiousness as a result of motivation and other effects and related overall motivation to this construct. Implications of this study are that students tend to leave after their first year, and these students tend to have lower overall ability as measured by ACT score, and are less motivated than other students for either education in general or for focus on their degree areas.

Other studies have reviewed factors related to success from the view of admissions decisions, success interventions and the ability of students to change behaviors once on campus. Dollinger (2008) considered the Big Five personality factors
and other behaviors to determine if students were subject to behaviors they could control or issues outside of their ability to change directly. This study found that 37% of the variability of their model was explained by the behaviors outside of students’ control, such as the innate behaviors of the Big Five. The Big Five personality traits: openness, agreeableness, conscientiousness, neuroticism and extroversion, have been tied to educational research for some time with conscientiousness being most strongly linked to academic achievement (O’Connor 2007, Bidjerano 2007, Poropat 2009, Beaujean 2011).

Certain expressions of the Big Five were effectively under students’ control such as attendance and project completion, but these only explained 6-10% of the variance in GPA. They also found that conscientiousness was the most important factor related to student success. Allen (2010) recommends interventions that target improving these uncontrolled elements of a student’s personality. By improving conscientiousness, for instance, it is posited that the overall retention of students could increase simply by adjusting efficacy and motivation through this element. Sinha (2011) recommends adjusting admission criteria altogether. Assuming that interventions may not work, but by setting the standards of admission to mirror the culture, dynamic, and strengths of a university, students will be better matched to thrive in an appropriate environment.

Definitively, personality and innate non-cognitive or psychosocial factors play a role in college retention. Students’ efficacy and motivation play primary roles in their ability to fulfill the requirements of a degree through to completion. Motivation itself is a mediating factor across many socioeconomic backgrounds and is a common factor of success for students of many intelligence levels and family dynamics (Steinmayr, 2012). But there is still much debate in how to approach the merging of these factors with the
cognitive factors and how to use this information. A recent study has called for an overall alignment of the various areas of research to generate more effective interventions and understanding of the most comprehensive view of retention (Moreira, 2013). There has been little research into the effects of interventions. How to focus the model used to measure the non-cognitive factors is still very much open to discussion. At this point it is most likely that focusing on efficacy and motivation, and the factors related to these personality traits will bear the most fruit.

2.3.5 Psychosocial Factors: Motivation, the five factor model, and decoupling efficacy

In its most basic division, motivation is either extrinsic or intrinsic. Extrinsic motivation is a force that moves people to act that is external to them. This may be the need for approval, or a reward of some kind that is given to them for achieving some goal. In education, the most common situation would be a reward to a student for achieving certain grades, or the approval they may get from teachers or parents. Intrinsic motivation is internal. In some ways this is an innate driver that the individual feels to act based on his or her own self-interests (Ryan, 2000).

The impact of intrinsic and extrinsic motivation has been studied at length, and much of this work has shown that intrinsically motivated individuals have many advantages over extrinsically motivated people when it comes to educational attainment (Lei, 2010). That is not to say, however, that intrinsic motivation is without any negative attributes; but being self-motivated seems to propel students toward a goal and they are less deterred from the goal when setbacks occur. Moreover, intrinsic motivation is
positively correlated to factors directly related to success such as expectations for success and individual needs for success (Story 2009, Goodman 2011, Ratelle, 2007). Often there is a fleeting bump in performance associated with programs designed to increase extrinsic motivations. Less motivated students are targeted and encouraged through reward and constant praise. This bump is short-lived as praise cannot be supplied indefinitely.

Intrinsically motivated individuals, though, seem to be moved by self-determined outcomes. They can be setback, however, if they are somehow confronted with situations where external influences become a predominant factor in the context of their work (Deci 2001, Cameron 1994). For example, if an intrinsically motivated student is overwhelmed with praise for their work for every instance of good performance, as with programs targeting under motivated students, they will begin to seek the praise rather than doing the work for their own self-interests. It is difficult, then, for them to persist when faced with challenges to their immediate satisfaction (Yeager, 2012).

As previously stated, it is important to acknowledge that students who autonomously elect to enter engineering are more likely to do so as an intrinsically motivated action, while providing a carrot for a student to opt into the field is largely extrinsic in nature. The implications of this are important with respect to the purpose of this research. If we are to assume that recruiting students is far less effective than retaining them, the fact that extrinsic motivation drives the recruited student is especially important given the following research will show this is a weaker and ultimately less effective form of motivation with respect to retention in the field (Jones, 2010). Put simply, recruited students, even if higher quality by traditional measures, are more likely
to drop out of the major (Guiffrida, 2013). Furthermore, the type of motivation required for success in engineering may be specific from that required in other fields (Breen, 2002) leading to even further possible negative effects of this recruitment model.

If it is possible to direct self-motivated individuals away from their natural tendencies and toward an external locus of control, it would follow that it might also be possible to direct externally motivated individuals toward a more intrinsically motivated direction when given proper focus on this intent (VanNuland, 2012). In fact, Wagner (2012) performs a meta-analysis on the research in the field and discovers several intervention methods that aid in increasing motivation in students’ higher education. The improvement they found was highly situational and relied heavily on the student having interest in achievement in college in general, not specifically one major over another, so the improvement may be limited. The age, gender, grade and major of students also impacts the academic motivation and study skills, and the intervention needs to mirror these differences (Lijun, 2011). Robbins (2009) also builds the case for interventions, but is more specific about the types of improvements necessary to increase student retention and in the specific context of psychosocial factors (PSF). In this construct, the mediating role PSF provides a guiding context for how the intervention plays out with each type of individual.

Without intervention, the prevailing natural trend in motivation over the course of a year is toward less beneficial types of motivation. While many students remain firmly planted in an intrinsically motivated state, many students will begin to focus on less beneficial motivational constructs as a natural course (Hayenga, 2010); implications for college engineering are obvious. As students move forward in their curriculum, it is
increasingly difficult for students to remain strongly motivated in their curriculum, especially when faced with courses and teachers that do not foster positive forms of motivation. So intervention, as a standard course, should be applied throughout the curriculum as a basic pedagogy especially in math courses (Ali, 2011).

There is a complicated connection between self-identity and academic pursuits. How individuals see motivation and how they describe their self-efficacy are not independent from their self-awareness (Pekrun, 2006). In the broader perspective, when considering the whole student (academic aptitude, achievement, and their personality traits) the interconnectedness of these mechanisms becomes more apparent. Meriac et al. (2012) studied how work ethic related to college GPA along with standardized test scores and GPA. Their findings confirmed that motivation and self-efficacy play a role in college achievement, although they did not directly measure motivation or efficacy. The related concept of work-ethic is a direct offshoot of these personality factors. Kappe (2012) suggests a similar model of utilizing achievement and intelligence measures, but also uses measures of motivation, efficacy and the Big Five personality traits. Komarraju (2005, 2009) investigated the connection of the Big Five and motivation, and found that each of the five personality types had some degree of connection to different types of motivations. This further explains the correlation between personality factors and retention, as the research has shown that specific motivation types correlate to academic performance.

The available research suggests knowledge of the Big Five aids in predicting the motivation of the individual (Hazrati-Viari, 2011). When paired with intelligence factors the Big Five can provide significant explanatory value for the variability in educational
success indicators (Kappe, 2012). While conscientiousness has a direct impact on academic performance, and in some ways motivation, neuroticism has additional predictive value when efficacy is used as a mediating factor (2012). Research has also shown extroversion has some correlation to success, but that is in the context of a broad definition of success (Wang, 2013). Openness and agreeableness have been correlated to learning styles, but again that is a context key that adds an additional step away from directly linking to success (Komarraju, 2011). In all, it is apparent that conscientiousness and neuroticism play significant roles in academic achievement, and adding measures for efficacy and academic aptitude (ACT score) and previous achievement (high school GPA) increase the value of these models.

The Robbins (2009) study provided a framework for future directions of this literature review. Aligning motivational and self-efficacy beliefs with interventions to improve study skills, general self-concept and academic interests provided a foundation for understanding the interrelations of individual personalities and the factors directly related to student retention. This connection between efficacy, motivation and how these factors are measured are an important cornerstone to the bulk of future papers reviewed and was a turning point in the research. To this point the focus had been on the factors related to retention, leading from cognitive factors, which remain important, to non-cognitive factors that were not highly correlated to retention. This led to discovering motivation as a main factor that applies to the entirety of the student population and shows strong correlation to retention. Subsequent literature searches focused on greater understanding of motivation, efficacy, psychosocial factors and their relationships.
Tracing the development of the model tested in Robbins (2009) back to the original meta-analysis by Robbins (2004) provided the developmental source for a comprehensive survey. A vetted survey is needed to provide a model that includes the most important factors revealed in this review of the literature and that aligns well with the data available to analyze students at many non-selective engineering schools. For this research, this is the most interesting population to focus on for increasing retention as outlined earlier. Le (2005) begins the development of the Student Readiness Inventory (SRI), refining the factors that best fit the overall model until finally arriving at a representative survey model. Peterson (2006) further tested the model against a standard measure of the Big Five personality factors and found that the SRI provided greater explanatory value when considering college GPA. Additionally, the study found that the values of conscientiousness, extraversion and neuroticism were well represented by values in the SRI. This was further supported by Robbins (2006) where it was asserted that the SRI accounted for the important factors of the Big Five with additional psychosocial factors included. This study also provided an interesting note, that there was not a strong correlation between self-efficacy and persistence. Further literature shows conflicting results, leading to more questions motivating this research. Finally, Komarraju et al. (2013) provides more insight into the connectedness of the SRI with potential motivation effects. Of specific interest is their assertion that high/low ACT students are different in their behaviors and outcomes than high/low high school GPA students. They provide some insight into the need for future research into the role of efficacy, leading to the continued review of efficacy.
In all, it seems that the SRI provides a well vetted and predictive model for the analysis of student success. The comprehensive nature of the survey and its accessibility are also important. Utilizing this survey mechanism provides comprehensive coverage of the factors related to success, when supplemented by high school GPA data, ACT scores and potentially, an additional measure of academic efficacy.

2.4 Efficacy

The concept of efficacy in relation to career and educational pursuits has been well researched. Efficacy being the individual’s belief in his own abilities related to four specific areas: performance, vicarious experience, verbal persuasion and emotional arousal (Bandura, 1977). The most fundamental view of efficacy is that the person behaves as an extension of their efficacy beliefs; this behavior is mediated by a level of outcome expectations and leads to the likely outcome based on these factors (Bandura, 1977). In terms of engineering education, students believe in their ability to a certain degree and react based on this belief. This reaction leads to an outcome in relation to GPA or persistence. Some who have strong efficacy will be proactive and interested students: they will be motivated and achieve in the field. While some with low efficacy will not try hard because they feel it is a lost cause: they will then withdraw from the major.

Of course the model of efficacy and its measures is much more complicated and has been thoroughly derived beyond this example. Efficacy measures have been compared to standardized test scores to determine the correlation between academic performance and efficacy. There were initially moderate connections between efficacy
and ACT scores in relation to career options, but also very high correlations between engineering career interest and efficacy (Betz, 1981). Further research showed a strong correlation to other measures of success and persistence, specifically in engineering pursuits. Students with high self-efficacy had significantly higher cumulative grade point averages in college and persisted in the engineering program for longer on average (Lent, 1984). This study also confirmed, to some degree, that efficacy and standardized test score are not highly correlated. Regression analysis in this study showed that there was no co-linearity between PSAT scores and measures of self-efficacy when using all three measures, along with class rank to predict educational achievement measured by GPA and average quarters of persistence. The efficacy measures were also independent, but also significant. These findings were later confirmed by another study comparing the self-efficacy measures and two other non-cognitive factors (Lent, 1987).

A later meta-analysis of the available research showed that the initial findings had been broadly accepted and confirmed. Self-efficacy had a significant effect on both persistence and academic performance as represented by GPA. In fact, this study showed that 14% of performance and 12% of persistence variability were explained by self-efficacy measures (Multon, 1991). This connection between performance and persistence was extensively explained by Lent (1994). This study demonstrated the connection between an individual’s self-efficacy and decision to pursue and persist on a path while being successful. Put simply, students will choose a path, degree program or career that they feel works well with their perceived strengths. Some may pursue areas outside their strengths, but will find it harder to be successful and to persist through adversity.

Findings from this study and the preceding studies lead to greater refinements in the
literature in relation to types of efficacy and subject specific efficacy which will be discussed later.

The focusing and specificity of survey design is apparent in more recent research. Specifically, efficacy led to anticipated outcomes of performance. As a result students began to make career decisions based on their anticipated success in an area, formed through their belief about their ability in that area. This research was specifically targeted to engineering students (Lent, 2001). Additional study focused on the efficacy in relation to motivation and goals. Mastery, performance approach and performance avoidance goals were measured and then compared to efficacy measures after early course grades were presented to students. Efficacy was strongly linked to goal types, showing that low efficacy and high efficacy had opposite impacts on these types of motivations based on the type of grade given to the student (Shim, 2005). This further supports the findings that efficacy and persistence are correlated.

Additional research into more comprehensive models of student retention supported previous findings, that ACT scores and efficacy are not highly correlated, but also revealed that when efficacy is significant when measured. Gore (2006) found significant correlation with persistence when measuring efficacy after the end of the first semester, but when measured at the beginning of the term, there was weak correlations. The model included the use of ACT, and the efficacy component of the SRI described in section 3 of this chapter. Also noteworthy is that the efficacy measure of the SRI correlated to ACT score, showing there are significant differences between efficacy measures.
That efficacy is strongly correlated to persistence and college GPA has been further supported by additional recent research (Elias 2007, Brown 2008, Zeldin 2008, Lent 2008, Conklin 2013, Mattern 2010). Additional relationships between efficacy and motivation have also been reviewed connecting conscientiousness and self-efficacy, finding a strong supporting link between these measures in regards to academic outcomes. This further supports the use of the SRI tool in coordination with an additional measure of efficacy added to the model (Capara 2011, Brown 2011). Also, specific attention has been paid to the student type being surveyed. As previously discussed, the first-generation student has less success in college than second-generation. Efficacy plays a role in this process: where the previous work was mostly qualitative, the measures provided by Vuong (2010) show that the lack of understanding in the qualitative study may be expressed in the efficacy of the student. It is also worth noting that research has shown a connection between self-efficacy and the belief that intelligence is either innate and fixed vs. malleable and subject to mastery goals, as previously discussed in the context of motivation. Findings show that those with low self-efficacy believe intelligence and learning are fixed. In contrast, high efficacy individuals work toward mastery goals believing they will adjust to the challenge presented to them (Komarraju, 2013). This fits well with the motivation research which shows that when students begin to learn that learning is not fixed, they become more motivated. Conscientiousness plays a key role in this process of overcoming adversity. In all, it has been thoroughly resolved that efficacy plays a role in success, and from a career-outcome perspective, recent literature supports the connection between efficacy and motivation as well as outcomes.
Family background and support have also been investigated in the context of efficacy. As before, there was only a weak link between these factors, but even when examined in the context of family support, efficacy was determined to be a strong predictor of success (Weiser 2010, Restubog 2010). Parental involvement was confirmed as a key addition to career goals when coupled with efficacy. When parents provide support for a career choice and outcome expectations there is a positive correlation to choosing math and science career fields (Byars-Winston, 2008).

To return to the intended goal of increasing persistence, finding that efficacy is connected to success is important, but does nothing to change the outcome. It then becomes important to understand if efficacy can be increased and if this increased efficacy can then lead to greater persistence. Luzzo (1999) reviewed the effects of self-efficacy based interventions in the context of math and science major decisions with groups of undecided students. The study showed that the intervention had a positive and meaningful impact on students’ self-efficacy and also major decision. Still some research has shown an increase in efficacy did not necessarily lead to an increase in interest (Cordero, 2010). Still the effect of intervention programs can definitively increase efficacy, at least in the short term (Breso, 2011) and precollege programming may have a significant effect on interest in the context of efficacy (Fantz, 2011). It has been determined that to gain the best overall improvement, teacher quality and learning environment must be incorporated into the intervention (Sawtelle 2012, Davidson 2012).
Given that it is possible to increase efficacy through an intervention, and that efficacy is strongly linked to college success, the remaining question is what efficacy types are most closely aligned to success in engineering? Lent (1991) found that performance (mastery) measures of efficacy were most closely linked to mathematics efficacy and career choice. Mathematics self-efficacy is strongly correlated to math problem solving ability (Pajares, 1994). But these studies were conducted with general type self-efficacy measures. Specificity of assessment could provide greater correlations to all aspects of mathematics problem solving as well as interest and career goals. The MSES-R used by Pajares (1995) provided a uniquely specific tool to examine three types of efficacy in relations to mathematics and provided greater correlation and explanatory value than other measurement tools to date. Other models provide differing connections to mathematics outcomes like correlations to ACT math scores (Lent, 1996), statistical mathematics using the CSSE (Finney, 2003), and the mathematics achievement test using the MSES not revised (Ayotola, 2009). Research into engineering specifically shows that certain aspects of engineering education are also related to efficacy, including engineering design (Carberry, 2010) and engineering problem solving (Lent 2007).

In the context of this literature review, a fairly complete model for predicting student outcomes may be formed through utilizing past academic performance (high school GPA), cognitive ability (ACT), PSF (SRI survey) and efficacy. Given the understanding of inputs related to student retention, the development of a model for increasing retention in engineering programs seems viable. With respect to the views that underprepared students may be the most viable demographic to increase the number of engineers, it seems that determining if it is possible it should consider these factors which
influence retention. Moreover, making the case for utilizing this student group will benefit from reviewing the production of previous efforts.

In business marketing, the concept that keeping a customer is much less expensive than creating a new one, is a widely accepted truth. Therefore, the best population of students to target for growing the number of graduates may be those who already enter into engineering fields, but are not completing the degree. These students have already shown an existing interest in the field, but are a part of the nearly 70% of students who do not graduate with a degree in that field. It is assumed that most of these students are underprepared. Unfortunately, insufficient research has been invested to determine if it is possible to get underprepared students to be successful in STEM at affordable and impactful rates.

Given the historical and current status of graduates in engineering, it is certain that this problem is not one of simply increasing recruitment efforts. To meet expected demand there must be additional interventions included in the engineering education process. Most obviously, increasing the graduation rates of historically underprepared engineering students at nonselective schools may provide inroads into the production of sufficient engineers while doing so in a cost-effective and efficient way. As demonstrated in the following chapter, retention of underprepared students has been greatly overlooked and may actually serve as the best method for increasing the number of engineers.
3.  LONGITUDINAL STUDY AND CURRENT DATA

In 2004, Wright State University introduced a new course to the engineering curriculum, EGR 101 Introductory Mathematics for Engineering Applications, which was designed to provide improved mathematics instruction and a faster route for students to enter into the engineering curriculum (Klingbeil et al, 2004). The course replaces many mathematics prerequisites for sophomore level courses thereby creating a just-in-time structure of the curriculum to meet course needs.

The course presents math problems in engineering context, covering content from algebra and trigonometry to calculus and differential equations. Anecdotal evidence supported success of the new curriculum, as initial data showed increases in early retention numbers and high satisfaction with the course from the students. Following years of success, the course solidified its place in the curriculum for engineering majors and continued success was apparent as retention rates among engineering majors continued to increase. It is unclear how much of the improvement in retention is due directly to the course itself, and how much may be attributed to the curricular restructuring. As a result of these trends a longitudinal study was requested to provide greater understanding of the effects of the course.

3.1  Student Demographics and findings

The students included in this study entered Wright State University directly from high school as engineering majors. All students were from Ohio high schools, and had taken the ACT. There were 1102 students in the analysis for this dissertation after
refining numbers from the original study shown in figure 7. Students from computer science and computer engineering were not included as those majors did not include EGR101 as a part of their required curriculum. The students were 82.9% male, 17.1% female; 79.8% white, 10.9% African American, 3.1% Asian, 4.7% did not provide and 1.5% other. The mean ACT math score was 24.46 and average high school GPA was a 3.32. Students that took EGR101 had slightly higher average ACT math scores and high school GPAs (26.2, 3.54) than the students that did not (23.98, 3.26). The student population prior to EGR 101 was for those students entering Fall 2000 through Summer 2004.

![Impact of EGR 101 on CECS Graduation Rates](image)

**Figure 7** EGR101 effect on graduation distributed by student ACT math score

Klingbeil and Bourne (2012) performed a longitudinal analysis of the effects of the EGR 101 intervention demonstrating the increase in student performance after the course. As shown in Error! Reference source not found., graduation rates in
engineering were significantly increased across ACT math ranges from 18 to 30 for students that entered Wright State University directly from high school. Questions arose from this study, including what specifically accounted for this increase in student retention through to graduation.

3.2 Determining significance and factor analysis

The literature has shown that ACT scores account for a considerable amount of the variability in persistence and GPA scores in college. But reviewing the available results from the EGR 101 intervention shows a mitigating effect of the EGR 101 course on ACT as a predictor of graduating in engineering. To further examine the effects of the EGR 101 course, a logistic regression was run comparing the components most commonly attributed to success in college with the outcome of ‘graduated in engineering’. Error! Reference source not found.8 shows the output of this original model. The logistic regression was used due to the binary resultant variable of graduated in engineering or did not graduate in engineering. Coefficients of the logistic regression correspond to the log odds of the event occurring given a one unit increase in the factor given by the equation \( \log(p/(1-p)) \). Additional consideration for sample size for each characteristic effect was taken to verify biasing was not an issue. The distribution across all effects was consistent and therefore biasing was not a significant issue for any effect.

Consistent with the literature, ACT math score and high school GPA were significantly associated with probability of graduation; however, both of these coefficients show negative associations. This leaves the likelihood of interactions among the variables. Gender also played a role as there was a weakly significant factor there as
well. What is important about this original output is that EGR101 is significant in explaining the variability in the model. In fact, a student taking EGR101 results in a log odds increase of 40%. Examining the interaction effects of factors often reveals additional valuable information about complex relationships. This was considered here to dig deeper into the effect of EGR101 on the student population and in particular to better understand the mitigating effect revealed by the graduation rates by ACT bin in Error! Reference source not found.. Additionally, the negative correlation between ACT and GPA with graduation also speaks to a likely interaction effect. Given the nature of logistic regression it was difficult to provide extensive explanation of the results when using GPA and ACT math as continuous variables. Further assessment resulted in the decision to combine ACT scores and GPAs into bins for a revised analysis.

The research done by Komarraju (2013) was useful in determining how to perform the regression utilizing bins for ACT math and GPA. For that study, student data was split into high and low bins for high school GPA and ACT score. This provided convenient comparisons of groups and more useful explanations of the nature of the interactions of the variables. Their research also provided an interesting conclusion that work ethic played a role for high GPA students and provided a great deal of discussion in the development of this dissertation. Considering the increase observed in the graduation rates of low ACT students after taking the EGR101 course as shown in Error! Reference source not found. 7, it is worth considering that perhaps the students overcoming deficiencies in ACT scores had high GPAs in high school. The resulting regression, Error! Reference source not found., shows bins of high school GPA, high being classified as above the mean GPA of 3.4 and ACT, high being above the mean ACT of
24. (See Appendix C – Decision Tree Analysis of MOAPs Cutoffs, for model and discussion regarding the generation of cutoff points for this analysis.) These mean/split values have been observed and used consistently for this study across cohorts for the studied period. Deviations from these splits may be considered in future research.

<table>
<thead>
<tr>
<th>Nominal Logistic Fit for GRAD EGR</th>
<th>Whole Model Test</th>
<th>Model</th>
<th>LogLikelihood</th>
<th>DF</th>
<th>ChiSquare</th>
<th>Prob&gt;ChiSq</th>
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</thead>
<tbody>
<tr>
<td>Difference</td>
<td>111.640</td>
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<td>223.2801</td>
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<td>Full</td>
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<tr>
<td>Reduced</td>
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<td></td>
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<td>RSquare (U)</td>
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<tr>
<td>Observations (or Sum Wgts)</td>
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<td></td>
<td></td>
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<td></td>
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<tr>
<td>Lack Of Fit</td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Source</td>
<td>DF</td>
<td>LogLikelihood</td>
<td>ChiSquare</td>
<td>Prob&gt;ChiSq</td>
<td></td>
<td></td>
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<tr>
<td>Lack Of Fit</td>
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<td>Prob&gt;ChiSq</td>
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<tr>
<td>Fitted</td>
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<td>0.0351</td>
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<tr>
<td>Effect Likelihood Ratio Tests</td>
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<td>DF</td>
<td>L-R ChiSquare</td>
<td>Prob&gt;ChiSq</td>
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<td></td>
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<td>Gender</td>
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<td>2.533</td>
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<tr>
<td>Underrepresented</td>
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<td>EGR 101</td>
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<td>1</td>
<td>21.792</td>
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</table>

Figure 8 Regression analysis, graduating in EGR v. primary demographic data
Figure 9 Regression analysis of graduating in EGR v. high school GPA and ACT

### 3.3 Grouping

The regression revealed an interesting interaction between EGR101 and ACT math score. For students who did not take EGR101, ACT was significant in predicting their successful graduation in engineering. However, when including the effect of EGR101, ACT math score becomes much less significant. As shown in the means comparisons in Error! Reference source not found., students that took EGR 101 have an essentially identical probability of graduating regardless of ACT score. The difference observed was not statistically significant.
Additionally, *Error! Reference source not found.* shows the separation of GPA, ACT Math and EGR101 groups. Of significant interest are students who have high GPAs and low ACT scores. The students who took EGR101 had significantly higher probability of graduating (61.1%) than students with high GPAs, low ACT math scores and did not take EGR101 (26.1%). This represents the greatest difference in the effect of EGR101 on any sub-group combination of students.

<table>
<thead>
<tr>
<th>GPA</th>
<th>ACT</th>
<th>Took EGR 101</th>
<th>Least Square Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>High</td>
<td>Yes A</td>
<td>0.667</td>
</tr>
<tr>
<td>High</td>
<td>Low</td>
<td>Yes A</td>
<td>0.611</td>
</tr>
<tr>
<td>High</td>
<td>High</td>
<td>No B</td>
<td>0.550</td>
</tr>
<tr>
<td>Low</td>
<td>Low</td>
<td>Yes B</td>
<td>0.462</td>
</tr>
<tr>
<td>Low</td>
<td>High</td>
<td>Yes B</td>
<td>0.422</td>
</tr>
<tr>
<td>High</td>
<td>Low</td>
<td>No C</td>
<td>0.261</td>
</tr>
<tr>
<td>Low</td>
<td>High</td>
<td>No C</td>
<td>0.233</td>
</tr>
<tr>
<td>Low</td>
<td>Low</td>
<td>No D</td>
<td>0.128</td>
</tr>
</tbody>
</table>

*Figure 10 Z-test, alpha=0.05 t=1.962, crossed effects of ACT Math and EGR101*

This data leads to further questions regarding reasons for the positive impact of EGR101. While it was intended to be a way to uncork the calculus bottleneck and connect engineering students with their major curriculum sooner, it may have other far reaching effects which depend on the demographics of the student. The mitigation of ACT math as an important factor in graduation shows some effect of EGR101 exists.
This may be due to course delivery, the increased flexibility of the curriculum or through its reduction of time to degree. However, this effect and possible explanations are also supported by the research in efficacy and psychosocial factors in education.

3.4 Access and Progress Toward Degree

It is important to consider the curricular timing of EGR101 as well. The Wright State model includes the benefits of accessibility to the engineering curriculum and gives the students a sense of true progress toward their degree. EGR101 has been used as a prerequisite for introductory engineering courses. The benefits of students beginning to move through the engineering curriculum while progressing through the math program, not after taking many math courses, cannot be overlooked.

As students move through a traditional engineering curriculum without the EGR101 intervention, the probability of dropping out of the engineering program is highest in the first two years. This is most often before these students ever take a single engineering course. Many have to take “filler” courses that do not count toward their degree program requirements. With the adjusted curriculum including EGR101, students were much more likely to make it through the two years immediately after EGR101. A probability model was developed to help understand the impact of sequencing and access via a curriculum including EGR 101. Define $Y_k$ to be Bernoulli random variable indicating whether a student withdraws from engineering in the $k$th term. Define $X$ as the random variable indicating the number of terms until a student withdraws from engineering. If a student graduates in engineering in the $n$th term then $X > n$. Assume that the probability of a student withdrawing in a term only depends on whether the
student has access to the engineering curriculum: \( p_{\text{non,egr}} \) is the probability of a student withdrawing if they have not yet taken an engineering course (without access). \( p_{\text{egr}} \) is the probability of a student withdrawing if they have taken an engineering course (with access).

The probability that a student withdraws in the \( k^{th} \) semester, \( \Pr[X = k] \), can be expressed by a collection of probabilities similar to a Geometric distribution, as shown in Figure 12 Probability of withdrawal by student access to engineering curriculum.

\[
\Pr[X = k] = \begin{cases} 
\text{without access} & k = 1: p_{\text{non,egr}} & \text{with access} & k = 2: (1 - p_{\text{non,egr}}) p_{\text{non,egr}} (1 - p_{\text{egr}}) p_{\text{egr}} \\
& k = 3: (1 - p_{\text{non,egr}})^2 p_{\text{non,egr}} (1 - p_{\text{egr}})^2 p_{\text{egr}} \\
& k = 4: (1 - p_{\text{non,egr}})^3 p_{\text{egr}} (1 - p_{\text{egr}})^3 p_{\text{egr}} \\
& \vdots \\
& k = 7: (1 - p_{\text{non,egr}})^3 (1 - p_{\text{egr}})^3 p_{\text{egr}} (1 - p_{\text{egr}})^6 p_{\text{egr}} 
\end{cases}
\]

Figure 12 Probability of withdrawal by student access to engineering curriculum

<table>
<thead>
<tr>
<th>Calculated Probability of Dropping and Retention with and without access</th>
<th>Probability of 1 term drop</th>
<th>Probability of Dropping</th>
<th>Cumulative Retention Rate after 7 semesters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without Access (no EGR101)</td>
<td>0.27</td>
<td>0.70</td>
<td>0.3</td>
</tr>
<tr>
<td>With Access (EGR101)</td>
<td>0.06</td>
<td>0.35</td>
<td>0.65</td>
</tr>
</tbody>
</table>

Figure 13 Per-term calculations of probability of withdrawal

The expressions in Figure 12 Probability of withdrawal by student access to engineering curriculum show \( \Pr[X = k] \) for \( k = 1 \) through 7, with access and without access. Without access students follow a traditional engineering curriculum with no access to engineering courses in the first three terms and access in each of the following terms enrolled. With
access students follow a revised curriculum with EGR101 in their first term and engineering courses in each term thereafter. This model was calibrated using retention data from 2000 through 2010 using all engineering students that entered Wright State during that time. This is data from the same time period used in the analysis from Chapter 3. During this time period the overall 7-term retention rate for students in the traditional curriculum was 0.3, leading to an estimate for $p_{non, egr}$ of 0.27. For students from Fall 2006 to Spring 2010 who followed the revised curriculum, the 7-term retention rate was 0.65, this included the inclusion of an additional mathematics intervention course, EGR199, a course designed for less prepared students. Together with the estimate of $p_{non, egr}$ this leads to an estimate for $p_{e gr}$ of 0.06.

Based on this model of retention, Figure 14 shows the term by term retention of students in the engineering curriculum based on available data. Because of the high rate of withdrawal for students without early access to engineering, the overall retention rate of students with EGR 101 in the curriculum is much higher.

![Fraction of Students Remaining by Term](image)

Figure 14 Retention of students by term with and without EGR101
Based on the results and discussion of this study, there are two major findings related to the implementation of EGR101: The first is the apparent mitigation of the ACT score in relation to graduation outcomes. The second is the curricular accessibility and progress toward degree. The available literature and existing measurement instruments provide some guidance toward a more precise explanation for the mitigation of the ACT impact. There is less clear guidance in the literature and in existing measurement instruments for more precisely explaining the sequencing/access impact of EGR 101 as a curricular intervention. The following chapters focus on studying psychosocial effects and the impact of EGR 101. In-depth study of the effects of access and progress toward degree are topics left for future research.
4. Study Overview and Primary Model Development

Given the difference in graduation rates exhibited by students who completed EGR101 versus the students who did not, it may be likely that the course effects the student population in an unknown way. Considering the overall effect that student efficacy and psychosocial factors have on student success it may be possible that it is these factors that are being changed by the EGR101 curriculum or instruction, and that this change is what is causing (or at least contributing to) the increase in graduation rates.

To date, there have been small studies of students taking the EGR101 curriculum at other institutions and the efficacy of these students has shown to increase after taking the course (Burnham 2012, Barker 2012), but it is unclear if this change in efficacy would result in the overall improvement in graduation rates that were demonstrated by the longitudinal study of EGR101 at Wright State University. Both of these studies used the MSES-R efficacy survey tool to measure the increase in efficacy, using the same tool before and after the course. In considering the lasting effects of an efficacy change, not just a bump in mastery of a finite sample of material, it seems that an evolving survey tool should be used. Additionally, it was shown that the portion of the survey that had the greatest change was that of mathematics problem solving, showing mastery of the problem sets or skills.

Several research goals were developed to better understand the results shown by implementing EGR101. Given the background research on efficacy and psychosocial
factors in education, the following goals were formulated to discern the effect of EGR101 on students. These goals were studied in the context of students’ mathematics education efficacy and their personality traits related to college education.

4.1 Study Purpose, Design and Goals

Study 1 – Engage

Goals:

A. Obtain data from students through the Engage survey tool from ACT inc.

B. Test the hypothesis that students in the four groups separated by mean ACT and GPA are different in how they assess factors related to academics including findings of the psychosocial factors: Study Skills, Academic Discipline and Efficacy.

C. Infer how differences discovered in B play a role in the effectiveness of EGR101 with regards to student retention through graduation in engineering.

Study 2 – Efficacy

A. Develop a survey mechanism to accurately record student efficacy in mathematics and engineering.

B. Validate the survey tool from the data collected; to determine if the survey components provide adequate feedback for assessment of question levels and consistency among survey results.

C. Analyze the data to determine the nature of any change from the pre and post survey represented in the student responses.
D. Align any conclusions with those of the Engage survey to further explain the previous findings regarding the success of EGR101.

4.2 Study 1 - Engage

While EGR101 was primarily intended to be a way to uncork the calculus bottleneck and connect engineering students with their major curriculum sooner, it may have other far reaching effects which depend on the characteristics of the student as well. In light of the available research on efficacy and other psychosocial factors of student populations, it was hypothesized that EGR101 had a dramatic impact on some aspect of the students’ non-cognitive abilities (Komarraju 2013). This is indicated by the mitigation of ACT math as an important factor in graduation rate.

Initial insights into the underlying traits of these four groups of students suggest that work ethic may play a role in the increased graduation rates for high GPA students regardless of ACT score. In regards to the shift observed (due to EGR 101) in the graduation rates of low ACT students with high GPAs, it is worth considering that students overcoming deficiencies in ACT scores had high GPAs in high school due to this stronger work ethic. (Komarraju 2013, Robbins 2004) Motivation may also be a contributing factor in success of students. Further analysis of traits like motivation and work ethic, along with other psychosocial factors is necessary to fully discern what factors are at play in regards to the effectiveness of interventions like EGR101 on different student populations.

To differentiate ACT/GPA factors from the contributing psychosocial factors we define ACT and GPA to be Measures of Objective Academic Performance (MOAPs). We
focus on the adjective *objective* because of the wide acceptance of ACT and GPA as metrics for past student success. We also wanted to consider less objective, personality-based factors i.e. psychosocial factors. Psychosocial factors require a more subjective approach to assessment and interpretation. To our knowledge, no research has attempted to ascertain if students separated by different levels of the MOAPS can be associated consistently with identifying characteristics in the subjective psychosocial factors. We designed a study to delve into this relationship.

**Error! Reference source not found.** sets the framework for a deeper study of the impact of EGR101. We hypothesized that the four groups (created by the separation of GPA and ACT at the mean) have psychosocial differences that help explain the disparate effect of the EGR101 intervention program. We hypothesize that these factors are connected to student performance in the MOAPs and also to student success in college. Working to understand the alignment of MOAPs with the psychosocial factors in our student population can help explain the effectiveness of programs like EGR101 and help design other interventions to support student success.

### 4.3 Study

Orienting the various psychosocial factors with MOAPs relies heavily on the measurement tool used to measure the psychosocial factors themselves. The focus of retention research has been mostly on MOAPS and only tangentially on psychosocial factors. The reason for this seems to be the low correlation between the various psychosocial factors and retention figures and the relative difficulty in measuring them. Therefore finding a tool that measures a wide range of factors was important for the
success of this study. The hypothesis that motivation is likely to be a significant factor driving student success, based on the findings from the initial EGR101 studies, served as a starting point for further research into psychosocial factors as a component of success. In keeping with a holistic approach to student success outside of MOAPs, finding a survey or study that captured a broad spectrum of student personality traits was a high priority.

As was discussed in chapter 2, the Student Readiness Inventory (SRI) is a well vetted survey instrument that assesses a broad range of personality traits. For example, Robbins conducted a meta-analysis for this tool (2004). The SRI provides a predictive model for the analysis of student success by employing a student’s self-assessment of psychosocial factors utilizing a survey with 108 questions. The comprehensive nature of the survey and its accessibility were also important to the overall success of this study. Utilizing this survey mechanism provides comprehensive coverage of the factors related to success, when supplemented by MOAPs and potentially an additional measure of academic efficacy.

The SRI tool is available for student surveying through the ACT Engage program. This assessment divides student personality traits into three domains: Motivation & Skills, Social Engagement, and Self-Regulation. Motivation & Skills is made up of six scales: Academic Discipline (related to student conscientiousness, how well the student feels they work toward their educational goals), Commitment to College (how determined the student is to completing a college degree), Communication Skills (interpersonal relationships and conflict resolution with others), General Determination (how well the student works toward commitments), Goal Striving (how strongly students
work toward personal goals), and Study Skills (how students assess their own belief in his or her skills at solving problems). Self-Regulation is made up of the scales: Academic Self-Confidence (the student’s belief in his or her ability to be successful in college) and Steadiness (how the student handles stress). Social Engagement is made up of social activity (social interaction) and social connection (feeling connected to the college community). (ACT 2012)

Of these categories, we chose to focus on the Academic Discipline and Self-Regulation scales in this research. We felt that it is unlikely that Social Engagement plays a role in differentiating the four MOAP groups or in explaining the increase in student success after EGR101 as social engagement is not a component of the EGR 101 course. We hypothesized that Study Skills and Academic Discipline are likely to play a role in the success of students with higher than average high school GPAs. Finally, we hypothesized that students with high ACT scores are more confident as they have proven their ability on a widely accepted standardized test.

Goals:

A. Obtain data from students through the Engage survey tool from ACT inc.

B. Test the hypothesis that students in the four groups separated by mean ACT and GPA are different in how they assess factors related to academics including findings of the psychosocial factors: Study Skills, Academic Discipline and Efficacy.
C. Infer how differences discovered in B play a role in the effectiveness of 
EGR101 with regards to student retention through graduation in 
engineering.

The study group consisted of students in the Fall 2013 section of EGR101 (now running 
under semester course number EGR1010) at Wright State University who were asked to 
take the ACT Engage survey during the first week of the term. 156 students took the 
survey and are included in the study group. This student group roughly matched the 
basic demographics of the longitudinal study of EGR101 (Klingbeil and Bourne, 2012). 
All students were originally admitted to Wright State University directly from high 
school, and came from an Ohio high school. All had high school GPA and ACT 
information available. The mean high school GPA of this study group was 3.63 and the 
mean ACT math score was 26.71. There were 36 females and 120 males.

Although the study group had GPA and ACT scores slightly higher than the 
institutional average, it seemed best to utilize the institutional averages of GPA 3.4 and 
ACT 24 to maintain uniformity in how the four groups were analyzed.

4.4 Results

Regression analysis of the data identified the following Engage Scales being 
significantly correlated to variation in GPA and ACT above and below the average score.

Academic Discipline: An ANOVA analysis in Error! Reference source not 
found. shows that both GPA and ACT scores play a role in the Academic Discipline 
measure (p-values of .0001 and .0209 respectively). Academic Discipline corresponds to
the individual student’s belief in how conscientious they are in regards to school work. In the study results, this measure is positively correlated with GPA and negatively correlated with ACT math score as shown in the means in Error! Reference source not found. Higher GPA students see themselves as working harder toward academic success than lower GPA, and higher ACT scoring students feel they are not working as hard as they could. Interestingly the average Academic Discipline score for High ACT/Low GPA students is far lower and significantly different from the other three student types.

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>Sum of Squares</th>
<th>Mean Square</th>
<th>F Ratio</th>
<th>Prob &gt; F</th>
</tr>
</thead>
<tbody>
<tr>
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<td>3</td>
<td>1195.60</td>
<td>398.53</td>
<td>10.01</td>
<td></td>
</tr>
<tr>
<td>Error</td>
<td>152</td>
<td>6048.99</td>
<td>39.80</td>
<td></td>
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<tr>
<td>C. Total</td>
<td>155</td>
<td>7244.59</td>
<td></td>
<td>&lt;.0001*</td>
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**Effect Tests**

<table>
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<tr>
<th>Source</th>
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<tbody>
<tr>
<td>HS GPA Score</td>
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<td>1</td>
<td>715.21</td>
<td>17.97</td>
<td>&lt;.0001*</td>
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<tr>
<td>ACT Score</td>
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<td>1</td>
<td>216.95</td>
<td>5.45</td>
<td>0.0209*</td>
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<tr>
<td>HS GPA Score*ACT Score</td>
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<td>1</td>
<td>33.036</td>
<td>0.83</td>
<td>0.3637</td>
</tr>
</tbody>
</table>

*Figure 15 ANOVA for Academic Discipline*
Academic Self-Confidence: Regression analysis in Error! Reference source not found. shows that GPA plays a role in the Self-Confidence of students which is the measure of students’ belief in their academic ability in the college setting. Higher GPA’s correlate to higher belief in their ability. It is as expected that the High ACT/High GPA students are at the top of this measure Error! Reference source not found. It is not expected that, while only the High/High and Low/High groups are statistically different from each other, it is GPA alone, and not ACT score, that is correlated to academic self-confidence.
Commitment to College: Regression analysis in Error! Reference source not found. shows that GPA is positively correlated to commitment to college, the measure of students’ determination to stay in college and obtain a degree. Students with higher than average high school GPAs are more focused on long-term success in college than their lower GPA peers. As with the Academic Self-Confidence measure, only high school GPA was significant in this analysis.
Figure 19 ANOVA for Commitment to College

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>Sum of Squares</th>
<th>Mean Square</th>
<th>F Ratio</th>
<th>Prob &gt; F</th>
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<tr>
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<td>Error</td>
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<td>39.64</td>
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<td>Prob &gt; F</td>
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<td>C. Total</td>
<td>155</td>
<td>6334.99</td>
<td></td>
<td>0.0538*</td>
<td></td>
</tr>
</tbody>
</table>

Effect Tests

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<th>DF</th>
<th>Sum of Squares</th>
<th>F Ratio</th>
<th>Prob &gt; F</th>
</tr>
</thead>
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<tr>
<td>HS GPA Score</td>
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<td>1</td>
<td>185.46</td>
<td>4.68</td>
<td>0.0321*</td>
</tr>
<tr>
<td>ACT Score</td>
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<td>1</td>
<td>62.33</td>
<td>1.57</td>
<td>0.2118</td>
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<tr>
<td>HS GPA Score*ACT Score</td>
<td>1</td>
<td>1</td>
<td>7.48</td>
<td>0.19</td>
<td>0.6646</td>
</tr>
</tbody>
</table>

α=0.100 t=1.65494

<table>
<thead>
<tr>
<th>GPA Score</th>
<th>ACT Score</th>
<th>Least Sq Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>Low</td>
<td>A 56.15</td>
</tr>
<tr>
<td>High</td>
<td>High</td>
<td>A 55.10</td>
</tr>
<tr>
<td>Low</td>
<td>Low</td>
<td>A B 53.93</td>
</tr>
<tr>
<td>Low</td>
<td>High</td>
<td>B 51.76</td>
</tr>
</tbody>
</table>

Figure 20 LS Means differences Student's t for Commitment to College

Study Skills: Although this regression is weakly correlated to ACT and to the cross factor of ACT and GPA, it is interesting to note the negative correlation between ACT and study skills. Students that have lower innate academic ability tend to focus on their study habits and how they formulate solutions to academic tasks.
The four Engage scales shown in this section provide a clear picture of the differences between students with regard to the four ACT/GPA groups that have been discussed. These findings support the hypothesis that there are differences between these groups that may have an impact on their educational performance.

### 4.5 Conclusions

**Goal B:**
From the regression analysis four distinct student groups are revealed and explained below. These groups make up the Academic Performance-Commitment Matrix (APCM) a cross section of performance measures (MOAPs) and personal academic commitment factors (confidence, commitment to college and motivation), formed by the quadrants created by the separation in the levels of the MOAPs (Error! Reference source not found. and Error! Reference source not found.).

**Reference source not found.** and **Error! Reference source not found.**

Mean Scores for Academic Performance-Commitment Matrix study groups

<table>
<thead>
<tr>
<th></th>
<th>ACT</th>
<th>GPA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Achievers</td>
<td>28.2</td>
<td>3.88</td>
</tr>
<tr>
<td>Support Seekers</td>
<td>22.95</td>
<td>3.73</td>
</tr>
<tr>
<td>Purpose Seekers</td>
<td>27.07</td>
<td>3.07</td>
</tr>
<tr>
<td>Purpose and Support Seekers</td>
<td>21.36</td>
<td>2.95</td>
</tr>
</tbody>
</table>

Figure 23 Mean scores for Academic Performance-Commitment Matrix study groups
Academic confidence rises with GPA, and also with ACT toward the upper right quadrant. Motivation, measured through the Study Skills and Academic Discipline scores, has a moderate negative correlation with ACT and a strong positive correlation with GPA. Commitment to College, also an indicator of motivation, is strongly positively correlated with GPA as well. Based on this overall view the following profiles of each APCM group were developed.

*Achievers* are defined by High GPA (mean 3.88) and High ACT (mean 28.2). This group includes the most self-assured and motivated students. It is natural to expect these students to be successful. However, they may not be more disciplined, goal
oriented or determined than the Support Seekers because they don’t have to be. Their
academic talent may allow them to be less conscientious than the Support Seekers;
however they are applying their abilities more dutifully than the Purpose Seekers. They
are likely to be more confident than all other groups and steadier overall. They are better
able to handle the rigors of college and this is represented in their higher graduation rates.

Support Seekers are defined by High GPA (mean 3.73) and Low ACT (mean
22.95). This group achieves positive outcomes led by their persistence and motivated
behavior. Despite not being quite as talented as Achievers, they outperform their
academic talent and score well with high GPA’s. This shows great discipline,
determination, and goal oriented focus. This group showed dramatic increases in
graduation rates through the implementation of EGR101, and this may be due to low
academic self-confidence when entering college which was overcome with help from the
course (more in Goal 2 conclusions below). This may stem from a belief that their lesser
academic talent may be an overall hindrance to their long term goals, and some
intimidation from the aspects of college that are still unknown to them. They likely have
better study skills than the other groups, especially the Purpose Seekers, who are not as
motivated to put forth effort and work towards a goal.

Purpose Seekers are defined by Low GPA (mean 3.07) and High ACT (mean
27.07). This group is generally unmotivated, and may lack discipline and commitment to
college. Additionally, this group may not have specific goals for themselves and, unlike
Support Seekers and Achievers, have yet to sincerely apply their academic skills in the
academic setting. With higher than average ACT scores it would seem these students
would be unlikely to have low confidence. However, they may not be very interested in
the courses they have taken to date nor understand their academic abilities and this overrides their sense of self. They may be higher in social engagement or other pursuits than their more motivated peers based on a lack of interest in academics. They have enough interest in being in college that social connections and these other pursuits may be a driving force.

*Purpose and Support Seekers* are defined by Low GPA (mean 2.95) and Low ACT (mean 21.36). This group generally scores the lowest in most areas, but because of the variety of issues this group faces, there may be no clear alignment with major problems in just one area. Students may be neither motivated, confident, nor engaged. They may lack study skills and may not have specific goals for themselves.

**Goal C:**
Because of the differences found in each of the APCM groups, it seems that EGR101 helped students overcome some of the generalized issues within each group and increased their graduation rates. Because the increase in graduation rates for *Support Seekers* is so high, it is evident that some element of the course helped them overcome an apparent deficiency in their academic ability. We believe EGR 101 is most likely to have helped the students deal with low academic self-confidence. Given the design, content and structure of the course, it is likely that these students gained belief in their ability to be successful in engineering.

Having a relatively small increase in graduation rates as a result of EGR 101, the *Purpose Seekers* were least impacted by the course. This also seems natural as having a lack of goals and motivation appears to remain as a problem for these students.
4.6 Discussion

The findings of this study reveal systematic differences in personality traits for students across the APCM as defined by the cross section of two MOAPs. Personality traits are correlated to the academic performance measures and provide a clearer understanding of why the impact of EGR101 was different for each group. These findings also provide explanation for the mitigating effect of EGR 101 on ACT score as a predictor of graduation rates, an effect that has contradicted traditional perspectives on student success. In fact, this research clarifies and reinforces ACT as an effective predictor of graduation rate. It further reveals the impact of EGR101 as a mitigating factor for the negative effect of low academic self-confidence for students at the lower ends of the ACT scale. Finally it quantifies the increase in graduation rates more precisely for other groups throughout the scale.

Interestingly, previous study of the SRI (Robbins 2006) showed low correlation between the self-confidence measure and student success, while it showed a strong correlation between high school GPA and academic self-confidence. Further study into specific self-confidence measures, such as mathematics self-efficacy, may provide greater understanding into how self-confidence may affect academic success. Previous research has shown a strong link between mathematics self-efficacy and academic success, and tying this to the APCM could be beneficial for fuller identification of differences across the engineering student population.
5. Study 2 – Efficacy

Goals:

A. Develop a survey mechanism to accurately record student efficacy in mathematics and engineering.

B. Validate the survey tool from the data collected to determine if the survey components provide adequate feedback for assessment of question levels and consistency among survey results.

C. Analyze the data to determine the nature of any change from the pre and post survey represented in the student responses.

D. Align any conclusions with those of the Engage survey to further explain the previous findings regarding the success of EGR101.

The efficacy survey utilized in this study is a refinement of the MSES-R. MSES-R does not provide sufficient engineering context, and is not useful as a tool to measure change in efficacy (Barker 2010, Burnham 2011). The refined instrument was not primarily intended to provide an absolute measure of a student’s efficacy. The goal was a tool that can be utilized to compare pre-course and post-course results or compare different students in one cohort.

The following analysis expands the insights from the Engage Survey whereby the efficacy measure was further developed through an understanding of the student groups.
based on mathematics-specific efficacy. Efficacy is best tested as a subject-specific measure (Lent, 2008). Given the varied nature of different engineering disciplines mathematics content present in all engineering disciplines provides a unifying basis to generally measure efficacy in engineering students. Where previous attempts at measuring the effectiveness of EGR101 through mathematics efficacy utilized non-context oriented questions, the revised survey developed for this portion of the research provides a tool designed around both mathematics content and engineering context.

Two survey instruments were used, one in the first week of the EGR1010 course in Fall 2013 (the pre-course survey), and one in the final week of the course (the post-course survey). The pre-course survey, shown in Appendix A, has three levels of questions with increasing difficulty, labeled ESY, MED, and HRD. Each difficulty level has six questions. In the post-course survey, shown in Appendix B, there are also three levels of questions with increasing difficulty. Identical questions from the pre-course survey were used for levels MED and HRD in the post-course survey, and a new level ADV was added. Students were asked to rate their confidence (on a Likert scale of 1 to 5) in their ability to solve each question given they were to take a course covering the type of question being asked.

ESY questions represent mathematics topics the students should have covered in previous courses as a prerequisite to EGR101. Topics in trigonometry, basic physics and algebra II were used.

MED questions represent mathematics topics taught in the first few weeks of EGR101. Students may or may not have seen these concepts in earlier coursework, but will certainly cover them by the end of the EGR101 course.
HRD questions represent information that students most likely have not seen in earlier coursework before EGR 101. This includes Calculus I and II concepts as well as those from introductory engineering courses like Statics and Circuits I.

ADV questions represent information that students mostly likely have not seen even after finishing EGR 101 and that are typically found in advanced level engineering courses (beyond introductory courses). Courses in thermodynamics, advanced physics, or later calculus courses cover these advanced concepts.

These surveys were used for two fundamental purposes: First, students are expected to assign identical questions on the two surveys with a higher confidence in the post-course survey. Second, students are expected to rate their confidence similarly on questions of similar difficulty, relative to their stage in the curriculum. Questions from the first survey are identified with a subscript 1 followed by the unique question number. Post-survey questions are identified with a subscript 2 followed by the unique question number. For example, MED question 4 will be labeled MED14 in the pre-course survey and MED24 in the post-course survey.

Goals B and C:

1. Students will increase their confidence in answering identical questions.
2. Students will increase in their confidence in answering matched levels of questions. (ESY-MED, MED-HRD, HRD-ADV)
3. The Survey instruments will show that students perceive the questions by difficulty of question type.
4. The change in student confidence will further support the APCM findings from the Engage Survey.
5.2 Testing the Pre-Course Survey

A factor analysis using Varimax Rotation of the first survey using a 3 factor assumption is shown below in Error! Reference source not found.. The goal was for students to accurately perceive three distinct difficulty levels. In reality students mostly assigned questions into 2 levels. ESY13 and MED16 were the only factors identified as being part of a third difficulty level. Error! Reference source not found. shows a factor analysis for the same responses using only 2 factors. ESY13 and MED16 are assimilated into the second factor in this analysis. The revised analysis in Error! Reference source not found. shows that two factors are sufficient for explaining the difference in student perception of the test question. While the expected three distinct factors did not emerge in the student responses, the students rated the difficulty of the ESY questions consistently, and grouped the MED and HRD questions into one level. This may be explained by the student’s ability to perceive differences in the question types based on their experience. ESY questions were prerequisite to the EGR 101 content. The other two types (MED and HRD) were not yet seen by many of the students and their difficulty was therefore perceived in the same way by the students.
In the three factor model, MED16 and ESY13 are separated and significant. For future iterations of the survey, it will be necessary to review the content of these two questions. Examining their similarities to each other and differences from the other questions of the same level should lead to an understanding of what caused the different student perception.

5.3 Testing the Post-Course Survey

Similar to the pre-course survey, the post-course survey results were analyzed using factor analysis. In this post-course survey analysis, there was more obvious alignment in two factors. MED and HRD factors were grouped together in student perceptions and ADV questions formed a second factor. This is in contrast to the pre-
course survey, where ESY questions were separate. In the post-course survey, all MED questions were grouped with most of the HRD questions. The results for two HRD questions were ambiguous with no significant alignment to one or the other factor.

As with the pre survey, the alignment of factors may be due to student perception. The students may see MED and HRD questions as easier after taking EGR101.

Alternatively, it may be that the ADV questions are just more difficult. Further study into the exact meaning behind the student answers is necessary to more precisely understand student perceptions. The observed grouping of questions roughly into the expected groups for similar question level is encouraging.

Next, regression analysis was utilized to analyze these components more globally, rather than question by question. This analysis yields a strong indication that the students
see the question types as different across the pre-course and post-course tests. **Error! Reference source not found.** shows results of a comparison of mean confidence levels for the four question levels given on the pre and post-course surveys. It is consistent with the design of the survey that the students rated easy questions highest (most confidence) to advanced questions lowest (least confidence).

<table>
<thead>
<tr>
<th>Level</th>
<th>Least Sq Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>ESY</td>
<td>4.570852</td>
</tr>
<tr>
<td>MED</td>
<td>3.3782933</td>
</tr>
<tr>
<td>HRD</td>
<td>3.1739049</td>
</tr>
<tr>
<td>ADV</td>
<td>2.9297997</td>
</tr>
</tbody>
</table>

Levels not connected by same letter are significantly different

Overall, the analyses of the pre and post-test support its use as a method for measuring the change in efficacy. The designed question levels are perceived by students to be significantly different. Therefore changes in student scoring between the pre- and post-survey should provide insight into the effect of EGR101 on student efficacy in relation to mathematics.

### 5.4 Efficacy Survey Findings

Regression analysis was used to determine how the student responses to the survey were associated with the timing (pre- or post), level of question (ESY, MED, HRD, ADV), and APCM group of each student. In the results that follow, the four APCM Groups are labeled A (Achievers), S (Support Seekers), P (Purpose Seekers) and P&S (Purpose & Support Seekers). The overall JMP analysis is shown in **Error! Reference source not found.**..
The level of question, timing, APCM group and the interaction of APCM with level and timing were all significant. This is strong evidence that the average student’s confidence reported for each question level was different, consistent with Error! Reference source not found.0. These results also indicate that the reported confidence level depends on the timing of the question. This supports the hypothesis that there is a change in how students perceive the difficulty of similar questions due to taking EGR101. Also significant was that the APCM group of each student affected their scoring. The significance of the interaction of APCM with both timing and level indicate a more complicated relationship linking the effect of EGR 101 on the perceptions within different APCM groups.

Error! Reference source not found. studies the relationship between APCM group and question timing in more detail.
The following conclusions can be drawn from the values observed in Error!

**Reference source not found.**

1. Achievers assigned the highest confidence in both the pre-course and the post-course survey. Surprisingly, the Purpose and Support Seeker’s confidence in the pre-course survey could not be distinguished from the Achievers confidence in the same survey. Other research has reported that students in this group may have abnormally high regard for their ability (Kamarraju, 2013)

2. Support Seekers reported the lowest confidence of any group (2.83) in the pre-course survey. In the post-course survey this group reported the second highest confidence, which was not distinguishable from the Achievers on the post-course survey. This change of 1.32 points is by far the most of any group between the surveys. This supports the very strong overall effect that EGR101 has on the Support Seekers. This confirms this study’s main hypothesis that Support Seekers gain the most from the curriculum of EGR101 because of the improvement in
Efficacy they receive from the course. The increase most likely accounts for the continued success they have through to graduation.

<table>
<thead>
<tr>
<th>Level</th>
<th>Least Sq Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>ESY,1 A</td>
<td>4.300</td>
</tr>
<tr>
<td>MED,2 B</td>
<td>3.933</td>
</tr>
<tr>
<td>HRD,2 C</td>
<td>3.711</td>
</tr>
<tr>
<td>ADV,2 D</td>
<td>3.367</td>
</tr>
<tr>
<td>MED,1 E</td>
<td>3.013</td>
</tr>
<tr>
<td>HRD,1 F</td>
<td>2.725</td>
</tr>
</tbody>
</table>

Levels not connected by same letter are significantly different.

Figure 32 LS means Student’s t for interaction of question level and timing

Error! Reference source not found. shows the analysis of the interaction of question level and timing. This figure further explores the findings in Error! Reference source not found. that show a significant difference between question levels.

The following observations are evident from Error! Reference source not found.:

1. The easy questions from the first survey were scored with the highest confidence of any question.
2. The ordering of student confidence is consistent with the designed question difficulty within each of the pre-course survey and post-course results. The easier questions within each survey were rated with higher confidence.
3. Confirmation of the hypothesis that students would score similar questions to be less difficult after taking the class compared to before. In comparison of identical questions, (MED, 1 versus MED, 2) and (HRD, 1 versus HRD, 2), responses from
the post-course survey were significantly higher than their pre-course survey counterparts.

4. The ADV questions in the post-course survey were scored significantly higher than the MED and HRD questions from the first survey. Overall, students felt more confident in their ability to solve problems after the course. This confidence extended to the more advanced engineering problems found in the ADV examples, which were well beyond the topics covered in EGR 101.

Error! Reference source not found. details the analysis of the interaction between the level of the question and the APCM group. The following observations are evident:

1. The confidence reported by Purpose and Support Seekers for the MED, HRD and ADV scores are concentrated and not significantly different. It appears that many of the students saw no difference between the questions. This may imply that the questions were perceived as universally hard. Alternatively, it is possible that they simply answered identically throughout the survey (3 for every answer). In support of the former interpretation, the confidence reported by Purpose and Support Seekers on the ESY questions is significantly higher. It is most likely that Purpose and Support Seekers saw the non-ESY questions as being equally difficult and indistinguishable, while still considering each question’s difficulty separately.

2. Purpose seekers’ reported confidence was not significantly different between the MED and HRD questions. Purpose Seekers scored ADV questions with the lowest confidence among the four question types, but the difference
between reported confidence on ADV and MED questions for this group was not significant.

3. The Support Seekers’ reported confidence on the different level of questions was consistent with expectations, i.e. they scored easier questions with a higher confidence.

4. The confidence reported by Achievers, Purpose Seekers, and Support Seekers on the ADV questions could not be distinguished from each other. All three groups reported very low confidence on these questions.

### Table 3: LSMeans Differences Student's t

<table>
<thead>
<tr>
<th>Level</th>
<th>Least Sq Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>A,ESY</td>
<td>4.942</td>
</tr>
<tr>
<td>S,ESY</td>
<td>4.814</td>
</tr>
<tr>
<td>P,ESY</td>
<td>4.323</td>
</tr>
<tr>
<td>PandS,ESY</td>
<td>4.204</td>
</tr>
<tr>
<td>A,MED</td>
<td>3.563</td>
</tr>
<tr>
<td>S,MED</td>
<td>3.410</td>
</tr>
<tr>
<td>PandS,ADV</td>
<td>3.396</td>
</tr>
<tr>
<td>PandS,MED</td>
<td>3.383</td>
</tr>
<tr>
<td>PandS,HRD</td>
<td>3.342</td>
</tr>
<tr>
<td>A,HRD</td>
<td>3.272</td>
</tr>
<tr>
<td>P,MED</td>
<td>3.156</td>
</tr>
<tr>
<td>S,HRD</td>
<td>3.103</td>
</tr>
<tr>
<td>P,HRD</td>
<td>2.979</td>
</tr>
<tr>
<td>A,ADV</td>
<td>2.887</td>
</tr>
<tr>
<td>P,ADV</td>
<td>2.802</td>
</tr>
<tr>
<td>S,ADV</td>
<td>2.635</td>
</tr>
</tbody>
</table>

Levels not connected by same letter are significantly different.

Figure 33 LS means differences Student’s t for APCM group and question level

The National Model of Engineering Education (NMEE) was developed to provide a useful tool to assess and experiment with changes in the national collegiate system. The model was designed, utilizing a system dynamics approach, to provide objective data to compare national-level outcomes that might be gained by adjusting recruitment and retention. This capability will be used to support the formation of strategies to achieve national goals for numbers of engineering graduates. The goal is to provide support for strong emphasis on retention as the best opportunity for growth in the production of engineering graduates.

To achieve a usable approximation of graduates the NMEE first needed to be an accurate estimation of engineer output. Because the available historic data on graduation rates does not include breakdowns by school or by APCM student composition, this data was obtained from several sources. Overall, the model is the best available measure of the aggregate output of US engineering schools.

The National Center for Educational Statistics provides data on large samples of students entering college by cohort year through the PowerStats program (NCES, 2013). Utilizing this data set, a table was generated providing the retention rates in engineering by selectivity of school. Figure 35 shows the table of students that began as engineering majors in one of the three tiers of schools. In Tier 1, very selective schools, 59 percent of the students that entered as engineering majors in 2004 were still engineering majors or had graduated as engineering majors in 2009. In Tier 2, moderately selective schools,
58.7 percent were retained, and in Tier 3, moderate or non-selective schools, only 30% were retained in engineering.

<table>
<thead>
<tr>
<th>High school grade point average (GPA)</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.5-0.9 (D- to D)</td>
<td>(%)</td>
</tr>
<tr>
<td>1.0-1.4 (D to C-)</td>
<td>(%)</td>
</tr>
<tr>
<td>1.5-1.9 (C- to C)</td>
<td>(%)</td>
</tr>
<tr>
<td>2.0-2.4 (C to B-)</td>
<td>(%)</td>
</tr>
<tr>
<td>2.5-2.9 (B- to B)</td>
<td>(%)</td>
</tr>
<tr>
<td>3.0-3.4 (B to A-)</td>
<td>(%)</td>
</tr>
<tr>
<td>3.5-4.0 (A- to A)</td>
<td>(%)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Admissions test scores (ACT or SAT)</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>400 &lt;= X &lt;= 1110</td>
<td>(%)</td>
</tr>
<tr>
<td>1120 &lt;= X &lt;= 1600</td>
<td>(%)</td>
</tr>
</tbody>
</table>

The names of the variables used in this table are:

<table>
<thead>
<tr>
<th>The weight variable used in this table is WTB000.</th>
<th>A</th>
<th>SS</th>
<th>PS</th>
<th>SPS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Source: U.S. Department of Education, National</td>
<td>0.363834</td>
<td>0.186069</td>
<td>0.129166</td>
<td>0.320931</td>
</tr>
</tbody>
</table>

Figure 34 Percent distribution of APCM groups across all colleges for students entering engineering
Figure 35 Percent of students who started as engineers remaining as engineers after at degree date by first school selectivity

The makeup of each school according to APCM student type was also important. Figure 36 shows the output of the PowerStats tool using the same data set from Figure 35, now generating the profile of each school based on APCM cutoff points. While the Tier 3 school data has some significance issues, it can be derived from the other data. This data provides a reasonable estimate for the purposes of model.
National Center for Education Statistics

Computation by NCES PowerStats Version 1.0 on 3/15/2014

Variance estimation method: BRR

First institution selectivity 2003-04 by Admissions test scores (ACT or SAT), High school grade point average (GPA), for Major when first enrolled in 2003-04 (comparable to 2006, 2009) (Engineering).

Filters

Major when first enrolled in 2003-04 (comparable to 2006, 2009) = Engineering

The names of the variables used in this table are: HCGPAREP, SELECTV2, MAJ04A and TESATDER.

The weight variable used in this table is WTB000.


Figure 36 Percent distribution of students by APCM breaks for GPA and ACT by school selectivity

Compiling the data as shown in Figure 37 provides a clearer picture of the APCM student parameters by school Tier. This follows expected outcomes as (1) Achievers are

<table>
<thead>
<tr>
<th>Tier 1 - Very selective</th>
<th>Tier 2 - Moderately Selective</th>
<th>Tier 3 - non or minimally selective</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>(%)</td>
<td>(%)</td>
<td>(%)</td>
<td>(%)</td>
</tr>
<tr>
<td>Admissions test scores (ACT or SAT) = 400 to 1110/ACT 1 to 24 Estimates</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total All EGR Students</td>
<td>29.2</td>
<td>39.8</td>
<td>9.3 !</td>
</tr>
<tr>
<td>Total</td>
<td>19.7</td>
<td>40.5</td>
<td>12.8 !</td>
</tr>
<tr>
<td>0.5-0.9 (D- to D)</td>
<td>‡</td>
<td>‡</td>
<td>‡</td>
</tr>
<tr>
<td>1.0-1.4 (D to C-)</td>
<td>‡</td>
<td>‡</td>
<td>‡</td>
</tr>
<tr>
<td>1.5-1.9 (C- to C)</td>
<td>‡</td>
<td>‡</td>
<td>‡</td>
</tr>
<tr>
<td>2.0-2.4 (C to B-)</td>
<td>‡</td>
<td>‡</td>
<td>‡</td>
</tr>
<tr>
<td>2.5-2.9 (B- to B)</td>
<td>6.5 !!</td>
<td>57.1</td>
<td>16.0 !!</td>
</tr>
<tr>
<td>3.0-3.4 (B to A-)</td>
<td>7.2 !</td>
<td>40.9</td>
<td>17.6 !</td>
</tr>
<tr>
<td>3.5-4.0 (A- to A)</td>
<td>34.5</td>
<td>38.9</td>
<td>9.9 !!</td>
</tr>
</tbody>
</table>

Admissions test scores (ACT or SAT) = 1111 to 1600/ACT 24 to 36 Estimates

<table>
<thead>
<tr>
<th>Total</th>
<th>46.4</th>
<th>41.8</th>
<th>5.7 !!</th>
<th>1.8 !!</th>
<th>4.4 !</th>
<th>100%</th>
</tr>
</thead>
<tbody>
<tr>
<td>High school grade point</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5-0.9 (D- to D)</td>
<td>‡</td>
<td>‡</td>
<td>‡</td>
<td>‡</td>
<td>‡</td>
<td>100%</td>
</tr>
<tr>
<td>1.0-1.4 (D to C-)</td>
<td>‡</td>
<td>‡</td>
<td>‡</td>
<td>‡</td>
<td>‡</td>
<td>100%</td>
</tr>
<tr>
<td>1.5-1.9 (C- to C)</td>
<td>‡</td>
<td>‡</td>
<td>‡</td>
<td>‡</td>
<td>‡</td>
<td>100%</td>
</tr>
<tr>
<td>2.0-2.4 (C to B-)</td>
<td>‡</td>
<td>‡</td>
<td>‡</td>
<td>‡</td>
<td>‡</td>
<td>100%</td>
</tr>
<tr>
<td>2.5-2.9 (B- to B)</td>
<td>‡</td>
<td>‡</td>
<td>‡</td>
<td>‡</td>
<td>‡</td>
<td>100%</td>
</tr>
<tr>
<td>3.0-3.4 (B to A-)</td>
<td>37.4</td>
<td>54</td>
<td>3.5 !!</td>
<td>0</td>
<td>5.1 !!</td>
<td>100%</td>
</tr>
<tr>
<td>3.5-4.0 (A- to A)</td>
<td>50.1</td>
<td>37.2</td>
<td>6.8 !!</td>
<td>2.5 !!</td>
<td>3.3 !!</td>
<td>100%</td>
</tr>
</tbody>
</table>

‡ Reporting standards not met.

! Interpret data with caution. Estimate is unstable because the standard error represents more than 30 percent of the estimate.

!! Interpret data with caution. Estimate is unstable because the standard error represents more than 50 percent of the estimate.

Variance estimation method: BRR

First institution selectivity 2003-04 by Admissions test scores (ACT or SAT), High school grade point average (GPA), for Major when first enrolled in 2003-04 (comparable to 2006, 2009) (Engineering).

Filters

Major when first enrolled in 2003-04 (comparable to 2006, 2009) = Engineering

The names of the variables used in this table are: HCGPAREP, SELECTV2, MAJ04A and TESATDER.

The weight variable used in this table is WTB000.


Figure 36 Percent distribution of students by APCM breaks for GPA and ACT by school selectivity

Compiling the data as shown in Figure 37 provides a clearer picture of the APCM student parameters by school Tier. This follows expected outcomes as (1) Achievers are
predominantly in the two more selective tiers, and (2) support and purpose seekers are nearly absent from Tier 1 schools. Interestingly, enrollment of Purpose Seekers in Tier 3 schools is similar to Tier 3 enrollment of Achievers, with only 8.6% of them in Tier 3 schools. This may show how the reliance on standardized tests as a measure of potential college success. Considering the nearly 40% attrition from engineering programs at the top two tiers, it may be further evidence that MOAPs considered in only one dimension are not the best indicator of potential. Further investigation into the graduation rates at the top two tiers would be helpful in understanding success of APCM groups by school type.

<table>
<thead>
<tr>
<th>Approximate Distribution of APCM to tiers</th>
<th>A</th>
<th>SS</th>
<th>PS</th>
<th>SPS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tier1</td>
<td>50.1</td>
<td>34.5</td>
<td>37.4</td>
<td>6.85</td>
</tr>
<tr>
<td>Tier2</td>
<td>37.2</td>
<td>38.9</td>
<td>54</td>
<td>46.3</td>
</tr>
<tr>
<td>Tier3</td>
<td>12.7</td>
<td>26.6</td>
<td>8.6</td>
<td>46.85</td>
</tr>
<tr>
<td>total</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

*Figure 37: Approximate distribution of APCM to school selectivity based on NCES data*
The model in Figure 38 represents the connections between students entering college who want to enter engineering degree programs (HSGrads). The model was developed in the AnyLogic modeling environment using the systems dynamics capability. The model is simulated starting with 125,000 students entering an engineering program each year, the most recent number of students entering engineering in a year according to NCES (2012). This new annual enrollment typically increases on an annual basis with an average increase of just less than two percent each year over the past five years. These newly enrolled students are parsed in the model by APCM type: A=Achievers, PS=Purpose Seekers, SPS=Support and Purpose Seekers and SS=Support Seekers. The percent distributed into each category is based on the numbers from Figure 34 using the parameters AEGRint, PSEGRint, SPSEGRint and SSEGRint. From here, students from each APCM group flow to school tiers based on the data from Figure 37.
resulting in overall annual enrollments in each school tier. Retention rates in the model for Tier1 and Tier2 are based on the rates in Figure 357. This results in the students that will graduate from Tier1 and Tier2 schools at the published rates, 95% and 85%, respectively. Tier3 schools were modeled after the Wright State student population from the study done in Chapter 3. The impact of implementing interventions like EGR101 may be extrapolated to all Tier 3 schools using the graduation rates observed at Wright State and discussed in Chapter 3. Each retention rate is connected to a slider tool in the user interface for the model that allows a user override to change the rates to allow a variety of specific modelling assumptions. The maximum for APCM graduation rates available in the model for Tier3 are the outcomes of student graduation after the implementation of EGR101, as reported in chapter3. The minimum graduation rates available in the model are based on students prior to the implementation of EGR101 at Wright State. The Tier1 and Tier2 sliders allow for retention minimums at 50% and maximums at the graduation rates of the schools in those tiers (100% retention in that major).

The following simulations demonstrate potential outcomes based on the scale of the implementation of EGR101, and the percent change in students wanting to major in engineering each year. Year one starts with 125,000 potential students. The model tracks the number of students in each subsequent year and provides an aggregate total of students that graduate in engineering, as well as those that do not after starting in engineering. Those that do not graduate in engineering may get another degree, or may drop out of college completely.
Figure 39 Cumulative graduates with annual input 125,000 no EGR101

Figure 40 Cumulative graduates with annual input increasing at 2% and no EGR101
Figure 41 Cumulative graduates with no annual increase in input and EGR101 fully in Tier 3 only

Figure 42 Cumulative graduates with input increasing by 2% annually and full EGR101 implementation in Tier 3 only
Figure 43 Cumulative graduates with no annual increase in input, full implementation of EGR101 in all Tiers

Figure 44 Rate of increase in input at 6.7% to match graduates needed of 750,000
Conclusions and Integrating Discussion

This dissertation has taken a systematic approach in reviewing the production of engineering graduates in the US and focusing on retention as a means to meeting demand. Based on results from EGR101 at Wright State as a retention program, the contributions in this dissertation focus on the drivers for increased graduation rates among students who took EGR101. Identifying these drivers using a statistically sound methodology supports a deeper understanding of engineering students. Analyzing the system level impact of improved retention programs has supported a greater understanding of the state of the engineering education system with implications to the overall graduation goals required for the engineering profession.

The initial findings determined that there are shortfalls in the prevailing understanding of engineering student success in college. These are tied closely to one-dimensional analysis of Measures of Objective Academic Performance (MOAPs). There is a necessity to move away from an overly simplistic assessment of preparation of students for college-level work. A multi-dimensional analysis based on a statistically sound engineering approach is necessary to accurately assess a student’s chances for success in engineering. Using regression analysis and a detailed study comparing mean outcomes considering multiple factors provides a rich framework for understanding students better. The series of studies discussed herein focuses on MOAPs that are commonly accepted as useful in assessing students (High School GPA and ACT Score). Using an engineering approach, this research has developed both an empirically based, as well as conceptually based, set of relationships between multi-dimensional student characteristics and their likelihood of success. This has led to defining a new description
of students, the Academic Performance-Commitment Matrix (APCM), that provides a conceptual basis explaining the changes in student success demonstrated after implementation of EGR101.

The APCM emerges from the analysis of student populations formed by considering psychosocial traits held in common among the students in each of the four groups. Utilizing the Engage Survey, students’ perceptions about learning were tied strongly to their MOAPs and this revealed four distinct student groups: *Achievers, Support Seekers, Purpose Seekers* and *Support and Purpose Seekers*. These groups are characterized by the psychosocial factors that explain the way they approach education. The connection between these distinct patterns of behavior and the results of the four groups in EGR101 is supported in this dissertation by background research, analyses of existing data, new surveys and analyses.

A higher high school GPA is indicative of a student’s greater commitment to college. A higher standardized test score shows greater belief in a student’s own ability to perform in certain academic subjects. This commitment, coupled with increased efficacy through academic intervention, is likely a major driver for the dramatic increases in graduation rates seen in students that take EGR101.

A study in the Fall of 2013 determined that students’ efficacy improved while taking EGR101 (under semester course number EGR1010), supporting the APCM framework. How each student group in the APCM perceived mathematics questions before and after the course, and how students felt they would do on future mathematics work before and after the course, also supported the APCM framework. Overall, students showed an increase in their perceived ability to answer mathematics questions after
taking EGR101. This increase was strongest in the *Support Seekers* group. This is the same group that had the highest increase in graduation rates in the longitudinal study. A multi-dimensional study of the level and timing of questions support the theory that APCM provides a framework for effectively describing and assessing the student population in open enrollment schools like Wright State.

Moreover, it is apparent that the implementation of the EGR101 course in other open enrollment institutions can provide an effective way to increase graduation rates to meet market demand. Recruitment alone will not meet this demand, as demonstrated through the use of the system dynamics model. Maintaining the current average increase in enrollments will not result in the desired number of engineers in future years unless retention is improved dramatically. Through an informed approach to improved retention, gains may be made at all levels of school selectivity which will help insulate the national production of engineering graduates output levels from any possible decrease in enrollments due to other factors.

Connecting student success strongly to fundamental characteristics of readily identifiable student groups can lead to targeted applications of retention and even recruitment efforts. Continuing to refine the parameters of the APCM and its relationship to student success will be helpful in better understanding the group dynamics and how best to apply intervention programs. For example, research into the psychosocial profiles of students in more selective schools may reveal another layer of student dynamics. Additionally, testing the splitting point for MOAPs in the APCM at selective schools may also be helpful. While the means used in these Wright State studies were based on the national means, this may not be the best way to divide students at selective schools. For
example, it is possible that the impetus to apply and the effort to get accepted at highly selective institutions results in most students at selective schools having a high Commitment to College factor. This may add another influence in the student psychosocial profile, so that splitting at different points might provide a better fit for these schools in order to achieve an understanding tailored to this student population.

Using the mean of high school GPA and ACT score as the splitting point in this research was based on functionality and ease of general understanding, more so than for the purpose of getting the highest significance in testing. A decision tree analysis (see Appendix C) showed that by optimizing the split parameters, the improvements in model predictions are relatively small. This does not mean that further analysis should be precluded for the sake of simplicity and applicability. Perhaps finding a methodology that may be readily applied across the full range of school selectivity tiers may be beneficial and supportable qualitatively as well.

The efficacy survey used in this dissertation may also be reviewed for possible improvements. While it was not designed or tested to provide an absolute measure of efficacy, the survey was able to serve its purpose in identifying a change in student perception of their ability to answer mathematics questions. The survey may, however, be used as an absolute measure of student efficacy in mathematics with further study. To do this, the survey should be vetted for accuracy and precision. Further understanding of the numeric values from the survey in terms of defining efficacy would be useful, including a potential one-to-one mapping of a survey result to an absolute efficacy scale.

The application of the APCM can be far reaching. The overarching purpose of this study was to determine why a particular outcome happened through the use of an
intervention (i.e. EGR101). But with the new information provided by this research, new methods for implementing first-year programs could be developed. Additionally, programs to target the *Purpose Seekers* may be developed with equally significant gains in retention as the *Support Seekers* increase through their gains in efficacy. The *Purpose Seekers* need to find a reason why they should be invested in their education. They are seeking motivation. While they understand they have the ability to do the work within the degree program, they are not motivated to persist through difficulty. What is more worrisome is that, unlike the *Support Seekers* that are earning degrees in other disciplines after transferring out of engineering, less motivated students are more likely to drop out of college altogether after leaving engineering.

As discussed at the end of Chapter 3, a thorough study involving the effects of uncorking the calculus bottleneck and providing access to engineering courses and faster progress toward a degree may be useful to discern specific impacts from EGR101’s curricular timing. However it is natural to assume that increasing mathematics efficacy prior to beginning math curriculum must be beneficial. The additional significance of early connection to the engineering curriculum would only have an additionally positive effect. Further, early access to engineering courses may have an impact on student motivation by bringing their long term career goals in engineering closer to reality. This would have significant impacts on *Purpose Seekers* and *Purpose and Support Seekers*, as these groups are especially under-motivated.

The creation of a program targeting *Purpose Seekers* could dramatically increase graduation rates of this group from non-selective schools. This effect could be large enough to mitigate the increasing cost of recruitment for all school types. *Purpose
Seekers make up a large percentage of selective school students as well. Further study into the retention rates of ACPM students in selective schools could prove beneficial. It is natural to imagine that other than Achievers, most students are having difficulty navigating the workload in highly competitive programs. The students other than Achievers make up a large portion of the 40% that leave engineering and change majors at competitive schools. Increasing retention rates in these programs seems feasible if desired. The debate, then, rests on the philosophy of success and retention in selective schools. Some feel that a “weeding out” of students needs to take place in the first or second year. The resulting attrition is natural in this context, and are therefore acceptable losses. Retention is far less a concern for these schools.

In all, it seems that the APCM should play a major role in future work at non-selective universities. The addition of EGR199 as a precursor to the EGR101 course for underprepared students implemented in Fall 2007. The longitudinal impact of this course has not yet been analyzed but is slated for 2015. The development of the APCM framework has provided a new lens to view the effects of this course. This course serves underprepared students entering engineering fields that are not yet prepared for EGR101, and makes the core engineering curriculum accessible to students placing as many as three math classes behind Calculus I.

Considering the APCM groups, it is likely that Achievers will not be a large percentage of this new course’s (EGR 199) enrollment. However, the other three APCM groups should be well represented. It is natural to build hypotheses about the effects of the new course on each of these groups. Does an additional course in the engineering curriculum have an effect on the Purpose Seekers as they appear to need greater
motivation? Based on their High ACT score, we believe they are already very capable. However, they will be enrolled in a course that does not match their apparent skill level and this may be difficult to accept. The *Support and Purpose Seekers* are likely to benefit most by this additional help and an increase in the connection to the curriculum. Many of these students begin the program more than three terms behind in their preparation, and EGR199 brings a connection to engineering during what could be considered time wasted far from their engineering goals. EGR 199 may provide *Support Seekers* similar benefits as EGR101 because of its similar design, although targeted at a different level of student preparation. The analysis of success would also benefit from the application of the efficacy survey used in Chapter 6. Determining if there is also an increase in efficacy from EGR199 would be beneficial. Also, it would be helpful to know if these increases mirror those observed with EGR101.

The APCM is being used to inform enrollment management decisions at Wright State University, as well as to help forecast student retention. Better predictive modeling may be generated by dividing incoming student cohorts into APCM groups. Further study into the retention effects by major in other colleges across universities may provide greater insight into the reasons behind student major changes or attrition.

Additionally, the model may incorporate other MOAPs as fundamental measures of student attributes. The vertical axis in the APCM represents innate ability, while the horizontal axis represents effort or commitment. The applications of the APCM to workforce analysis, other educational domains, and even athletics are readily apparent. Consider the aptitude of a sales force in relation to sales outcomes. If aptitude and effort are measured, then training may be adjusted to fit each group according to its unique two
dimensional skill assessment. In athletics, performance outcomes can be improved by determining the overall effort and ability of the individual and coaching can be refined to increase support or motivation accordingly. Finding well accepted MOAPS to fill these fundamental roles is crucial.

In all, there is wide applicability of the APCM model. Future refinements may be made through application of the model in various domains and analysis of results. The efficacy model may be studied and refined to provide an absolute measure of mathematics efficacy, and can be used to measure mathematics efficacy change in its current form. These tools can be widely used in educational decision making, forecasting and curricular development.
Appendix A – Pre-Course Revised Efficacy Survey

Mathematics Problems
Please indicate how much confidence you have that you could successfully solve each of these problems if exposed to the course material by circling the number according to the following 5-point confidence scale.

Confidence Scale:
No Confidence ←-----------------------------------------------→ Total
Confidence
1 2 3 4 5

<table>
<thead>
<tr>
<th>Problem</th>
<th>Confidence</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Solve the equation $2x^2 + 6x + 7 = 3$</td>
<td>1 2 3 4 5</td>
<td></td>
</tr>
<tr>
<td>2. If $V_L = \frac{100}{I}$; $V_R = 20I$; and $120 = V_L + V_R$, solve for current $I$</td>
<td>1 2 3 4 5</td>
<td></td>
</tr>
<tr>
<td>3. Compute the indefinite integral: $\int \frac{e^{x}dx}{\sqrt{1 - 4e^{2x}}}$</td>
<td>1 2 3 4 5</td>
<td></td>
</tr>
<tr>
<td>4. Find the area of a surface created by rotating the graph of $y = x^3$ from $x = 0$ to $x = 1$ about the x-axis.</td>
<td>1 2 3 4 5</td>
<td></td>
</tr>
<tr>
<td>5. If given angle A and side a, find the hypotenuse.</td>
<td></td>
<td></td>
</tr>
<tr>
<td><img src="https://via.placeholder.com/150" alt="Diagram" /></td>
<td>1 2 3 4 5</td>
<td></td>
</tr>
<tr>
<td>6. Find equivalent resistance for 2 resistors ($R_1$ &amp; $R_2$) in parallel if $R = \frac{R_1R_2}{R_1 + R_2}$</td>
<td>1 2 3 4 5</td>
<td></td>
</tr>
</tbody>
</table>
7. If you walk an 80° arc of the perimeter of a circle with radius of 100 feet how many feet do you walk? 1 2 3 4 5

8. Give the vector for: from (1,-8,4) to (1,2,-4) 1 2 3 4 5

9. If \( V_i(t) = RC \frac{dv_0}{dt} \) and \( V_i(t) = 12 \cos(100t) \) volts determine the output voltage \( V_o(t) \) assuming initial voltage is zero. 1 2 3 4 5

10. A cooling fin with height \( y \) and width \( x \) is approximated by the equation \( y(x) = -\frac{1}{4}(x^2 - 36) \). Determine the height and width of the fin. 1 2 3 4 5

11. Determine the equation of a plane that contains the points: \( P=(1,-1,3) \), \( Q=(2,3,4) \) and \( R=(0,-2,3) \) 1 2 3 4 5

12. For the equation \( h(t) = 96t - 16t^2 \), find both values of \( t \) for \( h=80 \) using the quadratic formula. 1 2 3 4 5

13. Determine the center of mass for the region bounded by \( y = 2x^3 \) and \( y = 3x \) 1 2 3 4 5

14. For a pendulum with a force applied to it \( f(t) \), and the angle from vertical resulting from the force satisfies the equation \( ml\ddot{\theta} + mg\theta = f(t) \), find the steady state solution \( \theta_{ss}(t) \). 1 2 3 4 5

15. If given velocities after 1 sec. and after 3 secs., and given \( v(t) = v_0 + at \) find the initial velocity and acceleration of an object 1 2 3 4 5

16. Sketch the graph for the conditions given in question 15. 1 2 3 4 5

17. Given initial conditions: \( RC \frac{dv(t)}{dt} + V(t) = 3, V(0) = -7.0V \); determine the transient solution \( V_{trans}(t) \) for a circuit. 1 2 3 4 5

18. A car traveling at 50mph skids to a stop taking 3.25 seconds. What is the skidding distance assuming acceleration is uniform? 1 2 3 4 5
### Mathematics Problems

Please indicate how much confidence you have that you could successfully solve each of these problems if exposed to the course material by circling the number according to the following 5-point confidence scale.

**Confidence Scale:**

<table>
<thead>
<tr>
<th>No Confidence</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>Total Confidence</th>
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</thead>
<tbody>
<tr>
<td>1. A 1.5 kg rock released from rest at the surface of a calm lake. If the resistance offered by the water as the rock falls is directly proportional to the rocks velocity, the rocks acceleration is ( a = g - C_d(v/m) ), where ( g ) is the acceleration due to gravity, ( C_d ) is the constant drag coefficient, ( v ) is the rocks velocity, and ( m ) is the rocks mass. Letting ( C_d = 4.1 \text{kg/s} ), determine the rocks velocity after 1.8 seconds.</td>
<td>1 2 3 4 5</td>
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<tr>
<td>2. If ( V_L = \frac{100}{1} ); ( V_R = 20I ); and ( 120 = V_L + V_R ); solve for current ( I )</td>
<td>1 2 3 4 5</td>
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<tr>
<td>3. Compute the indefinite integral: [ \int \frac{e^x , dx}{\sqrt{1 - 4e^{2x}}} ]</td>
<td>1 2 3 4 5</td>
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<tr>
<td>4. Find the area of a surface created by rotating the graph of ( y = x^3 ) from ( x = 0 ) to ( x = 1 ) about the x-axis.</td>
<td>1 2 3 4 5</td>
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<tr>
<td>5. A plastic film moves over two drums. During a 4s interval the speed of the tape is increased uniformly from ( v_0 = 2 \text{ft/s} ) to ( v_1 = 4 \text{ft/s} ). Knowing that the tape does not slip on the drums, determine (a) the angular acceleration of drum B, (b) the number of revolutions executed by drum B during the 4s interval.</td>
<td>1 2 3 4 5</td>
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</tr>
<tr>
<td>6. Find equivalent resistance for 2 resistors ((R_1 &amp; R_2)) in parallel if ( R = \frac{R_1 R_2}{R_1 + R_2} )</td>
<td>1 2 3 4 5</td>
<td></td>
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<tr>
<td>7. Consider a linear time-invariant system such that ( H(e^{j\omega}) = 1(1 - 12e^{j\omega})^2 ). If the input ( x[n] ) is periodic with period ( N_0 = 8 ), then determine the output Fourier series coefficient ( y_4 ) if ( x_4 = 9 ).</td>
<td>1 2 3 4 5</td>
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<tr>
<td>Question</td>
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<tr>
<td>12. A continuous random variable $X$ that can assume any value between $x = 2$ and $x = 5$ has a density function given by $f(x) = K(1 + x)$. Find $P[X&lt;4]$.</td>
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</tr>
<tr>
<td>13. Determine the center of mass for the region bounded by $y = 2x^3$ and $y = 3x$</td>
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<td></td>
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<td></td>
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</tr>
<tr>
<td>15. A fast food chain finds that the average time customers have to wait for service is 45 seconds. If the waiting time can be treated as an exponential random variable, what is the probability that a customer will have to wait more than 5 minutes given that already he waited for 2 minutes?</td>
<td></td>
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</tr>
<tr>
<td>16. A 3/4 inch diameter structural steel rod is subjected to an axial force of 1.5 kips. Determine the deflection of end B.</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>17. Given initial conditions: $RC \frac{dv(t)}{dt} + V(t) = 3, V(0) = -7.0V$; determine the transient solution $V_{trans}(t)$ for a circuit.</td>
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# Appendix C – Decision Tree Analysis of MOAPs Cutoffs

## Partition for GRAD EGR

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<th>RSquare</th>
<th>N</th>
<th>Number of Splits</th>
<th>Imputes</th>
<th>AICc</th>
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<tr>
<td>1</td>
<td>0.5658</td>
<td>0.5655</td>
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### HS GPA>=3.3

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<td>1</td>
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### ACT Math>=2

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<td>0.2925</td>
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### EGR 101(1)

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<tr>
<td>1</td>
<td>0.6483</td>
<td>0.6474</td>
<td>188</td>
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### Low Income

### Gender

### Underrepresented

### HS GPA>=2.9

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<th>Count</th>
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</thead>
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<tr>
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<td>1</td>
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### HS GPA<2.9

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<td>0.0727</td>
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Appendix D – National Model of Engineering Education

The National Model of Engineering Education (NMEE) was developed using the AnyLogic software system. This system allows for documentation of the development of the model design and for repeatability. The AnyLogic documentation information will be housed for future reference online at:

References

ACT, Inc. (2008). The relative predictive validity of ACT scores and high school grades in making college admission decisions. Iowa City, Iowa.


Hennessy, J. (2002). Teaching math and science: are students being prepared for the technological age? The CQ Researcher, 12(3) 697-720.


