AN EXAMINATION OF COGNITIVE AND NON-COGNITIVE FACTORS AND

ACADEMIC SUCCESS IN THE PRE-ENGINEERING CURRICULUM

AT A FOUR-YEAR SOUTHEASTERN UNIVERSITY

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VITA

Jennifer Lewis Bell, daughter of Ted Lewis, Jr. and Judy Lewis Dewell, was born October 27, 1975, in Thomasville, Georgia. She graduated from the University of West Georgia with a Bachelor of Science in Education (Special Education: Mental Retardation) in 1998, Master of Science in Education (Special Education: Interrelated) in 2002, and Education Specialist (Special Education: Curriculum and Instruction) in 2005. She taught special education in the Troup County (GA) School District for 8 years before leaving on an educational sabbatical in 2006 to attend Auburn University. In 2002, she received National Board Certification in Exceptional Needs. While at Auburn University, Jennifer worked as a graduate research assistant with Drs. Glennelle and Gerald Halpin. Her responsibilities included managing three grant-funded program evaluation projects, training data collection personnel, and analyzing program data. In addition, she served as the Tiger Eyes Director for the Auburn University Marching Band.

DISSERTATION ABSTRACT

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A large amount of empirical research has been conducted on academic achievement with college students. The empirical studies have revealed the significance of high school preparation, more specifically mathematical preparation, for academic success in post-secondary institutions; however, limited research exists for predicting academic success using cognitive and non-cognitive factors (i.e., self-concept, study habits, and inquisitiveness). The nature of engineering college courses tends to be quantitatively oriented, and calculus tends to serve as the gateway course for academic success within these majors. Conversely, non-cognitive factors significantly contribute to college mathematics achievement beyond standardized test scores or high school ranks.

The purpose of this study was to determine if cognitive factors mediate the effect of non-cognitive factors on quantitative grade point average and to determine if these cognitive and non-cognitive factors can predict admission status in engineering education. With College Freshman Survey results from a sample of 2,276 college freshman students who intended to major in engineering, the following statistical analyses were used: exploratory factor analysis, confirmatory factor analysis, structural equation modeling, and discriminant function analysis.

The structural model analysis revealed that cognitive factors (ACT math scores, high school math grades, and high school ranks) mediated the effects of non-cognitive factors (lack of confidence in academic ability, mathematical ability, difficulty with problem solving, and self-appraised abilities) on the quantitative GPA for the pre-engineering curriculum. The results of the discriminant function analysis suggested that participants who were admitted to engineering and those participants who left unsuccessful were classified correctly based on the cognitive and non-cognitive factors. The overall percentage of correctly classified cases was 51.6% with this analysis. Moreover, the model accounted for 29% of the variance in the quantitative GPA.

As a concluding part of this study, a secondary mathematics curriculum was developed to improve mathematical skills and problem-solving abilities. Within the Mathematics Curriculum for Advanced Mathematical Proficiency, the mathematical concepts are taught within real-world contexts. Each unit has an engineering connection to familiarize the students with the various fields of engineering.

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Style manual or journal used: Publication Manual of the American Psychological Association, 5th Edition.

Computer software used: SPSS 15, AMOS 7.0, Windows XP, and Microsoft Word 2007

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CHAPTER I

INTRODUCTION

Statement of Problem

According to the National Science Foundation (NSF) (National Science Board, 2006b), in 1983, 11.5% of the US college freshmen declared engineering as their intended major. This percentage slightly decreased to 9.6% in 2004. In addition to the trend of decreased interest, the rate of retention in the field of engineering has decreased. Of the 1983 college graduates, 7.4% of them earned a bachelor's degree in engineering. As a comparison, 4.6 % of the college graduates in 2002 completed a program in engineering. These percentages indicate that a disproportionately high number of students switch out of engineering majors because they either lose interest in engineering or have academic difficulties (Wulf & Fisher, 2002). From 1975 to 1999, the number of US students who completed bachelor's degrees in the natural science and engineering fields has dropped from 3rd to 14th compared to 19 other countries (National Science Board, 2006a). The declining interest in engineering fields and increasing attrition rates of pre-engineering majors have led to a serious shortage of engineers (Felder, Forrest, Baker-Ward, Dietz, & Mohr, 1993).

In the middle of the 20th century, President John F. Kennedy inspired a nation of scientists and engineers to win the space race after the Soviet Union's launch of Sputnik in 1957. These motivated individuals are reaching retirement age in the beginning of the

21st century, yet the declining interest and increasing attrition rates have reduced the number of scientists and engineers to replace them. This shortage of prepared scientists and engineers can be linked to poor preparation in mathematics and science instruction at the K-12 level (National Science Board, 2006a).

As an indicator of academic difficulties and confirmation of the NSF's conclusion, the percentage of college freshman engineering majors who reported the need for remediation in mathematics has increased since 1984, from 11.7% in 1984 to 14.0% in 2002 (National Science Board, 2006b). Between the years of 1992 and 2000, 20% of the freshmen who entered a doctoral institution took at least one remedial course in mathematics (National Science Board, 2004).

The student's decision to persist or change occurs during the first year of study at the college level. Often, this decision is based on successful completion of a gateway course (e.g., calculus) because the culture in these engineering courses tends to be quantitatively oriented (Gainen & Willemsen, 1995). Moreover, the knowledge gained from these quantitative courses is essential for the nation to compete successfully in today's global society (National Science Board, 2006a).

Possibly one reason college freshmen have problems in mathematics could be the apparent stagnation in mathematical ability for 12th-grade students. Since 1969, the National Assessment of Educational Progress (NAEP) has yielded assessments in reading, mathematics, science, writing, social studies, and the arts among 4th-, 8th-, and 12th-grade students from public and private schools. An examination of the 1999 NAEP average mathematics score for the nation revealed that the 9-year-old and 13-year-old participants continued to improve their scores each year, but the 17-year-old students' scores have remained stagnant since 1973 (Campbell, Hombo, & Mazzeo, 2000). Furthermore, 97% of the 17-year-olds achieved a level of 250 that indicated math proficiency in the four basic math operations and solving of one-step word problems. However, only 8% of all 17-year-old students scored at the 350 level indicating that they were capable of understanding and computing multiple-step problems. These data indicated that nationally 92% of all 17-year-old students who took the NAEP test could not comprehend or solve multiple-step problems.

More promising results of students' ability to complete mathematics problems were found in a study by Mitchell, Hawkins, Stancavage, and Dossey (1999). Using the same NAEP mathematics data, these researchers focused on the disaggregated data for students in 8th and 12th grade who took higher level mathematics courses. These researchers found that 30% of advanced 12th graders correctly solved problems involving two or more steps. However, all of the students who comprised the disaggregated data group indicated on surveys that their mathematics courses included a heavy emphasis on problem-solving skills. To support the findings of this NAEP study, of the 108,437 students who took the Advanced Placement (AP) calculus AB exam in 1997, approximately 59% of them earned a passing score of 3 or higher on a 5-point scale. Nine years later, in 2004, the pass percentage was nearly equivalent. These findings along with others, which have employed the NAEP data, indicate that many students lack proficiency when presented with mathematics problems that involve higher order thinking skills (National Science Board, 2006b).

Another indicator of mathematical achievement is the number of advanced mathematics courses taken at the high school level. Despite increasing percentages of advanced mathematics courses being offered at the high school level (i.e., 26.8% increase for statistics and probability and 13.4% increase for calculus since 1990), of the 2000 graduating class nationwide, only 5.7% of them completed a statistics and probability course, and 12.6% completed a calculus course (National Science Board, 2006b). Courses in mathematics, such as calculus, can open or close the gate for students interested in mathematical, scientific, or technological careers (Gainen & Willemsen, 1995).

Mathematics requires fundamental knowledge of concepts and procedures; however, it requires critical and analytical thinking skills. These mathematical problem-solving skills allow the students to apply their fundamental knowledge in various contextual situations. Students need to practice problem-solving skills in real-life situations. By practicing these skills, the students can increase their engagement with the content of mathematics, increase their ability to think critically, and increase their performance on higher order cognitive questions (Mitchell, Jakwerth, Stancavage et al., 1999; Wulf & Fisher, 2002). Based on these reasons, there is a need to prepare the students to solve contextual problems. Thus, they will be prepared for the ever-changing society (National Academy of Engineering, 2005; Litzinger, Wise, & Lee, 2005; Wulf & Fisher).

Education must academically prepare those potential engineers for the world of tomorrow (National Academy of Engineering, 2005). Anthony, Hagedoorn, and Motlagh (2001) suggested problem-solving and application skills would increase the likelihood of success in engineering (e.g., correlating the calculus and physics content). Unfortunately, traditional classroom instruction provides minimal preparation for inquiry-based learning or critical thinking during performance-based tasks.

The nation must prepare students in K-12 education for tomorrow's demands in the workforce and society. With continuing advances in technology, students must have a solid foundation in mathematics to be productive members in their communities (National Science Board, 2006a). External forces of society, economy, and profession challenge the stability of the engineering workforce. This instability affects recruitment of the most talented students into the engineering profession (National Academy of Engineering, 2005).

The NSF recommends further research regarding teaching and learning mathematics. For the students, the NSF recommends student exposure to science, technology, engineering, and mathematics careers through activities (National Science Board, 2006a). Similarly, Gainen (1995) and Klingbeil, Mercer, Rattan, Raymer, and Reynolds (2005) recommend early intervention programs in high school and a strong emphasis on application and appreciation of mathematical inquiry to increase student success in quantitative courses.

Mathematics ability is the strongest predictor of success in the field of engineering (LeBold & Ward, 1988). A correlational study conducted by van Alphen and Katz (2001) with electrical engineering majors supports this notion. The researchers found that a strong relationship existed between admission to engineering and academic background. Likewise, Klingbeil et al. (2005) pointed to a lack of high school quantitative preparation as the most notable factor that influences success in engineering.

Without a strong foundation in algebra, the doors are closed for subsequent mathematics courses (Edge & Friedberg, 1984; Klein, 2003).

Heinze, Gregory, and Rivera (2003) stated that high school mathematics sequences are very important for students interested in engineering. Similarly, Buechler (2004) found that grades during the first-semester calculus course predicted student performance in the engineering core classes. In addition to cognitive skills, students' attitudes relating to mathematical achievement can predict success in mathematics courses. These attitudes include expectation of success, their mathematical ability compared to their peers, and confidence in their own ability (House, 1995c). Similarly, success in engineering not only depends on mathematical knowledge and skill, but also it depends on the attitudes that the students bring with them to college. By measuring these initial attitudes, academic success can be improved. Students may have been academically successful in high school, but they may lack the confidence in their mathematical ability (Besterfield-Sacre, Atman, & Shuman, 1997).

Rationale

Several researchers have examined the relationship between cognitive factors [i.e., high school grade point averages (GPAs), standardized test scores, and high school ranks] and academic success in post-secondary education (House, 2000). Zhang, Anderson, Ohland, and Thorndyke (2004) examined 15 years of student data across nine universities. The purpose of the study was to determine the academic factors for degree completion in engineering. Using logistic regression, the researchers found that high school GPAs and Scholastic Aptitude Test (SAT) quantitative scores were positively correlated with graduation rates across all universities. The coefficient of determination

(R^2 = .126) indicated that other pre-existing variables would account for the variance. These results supported the findings of Gilbert (1960) who found that standardized test scores could not be used as the single predictor of success in engineering. Factors other than academic aptitude should be examined to predict graduation in engineering. Smith and Schumacher (2005) suggested the additional research with mathematical ability, interest, study habits, and academic self-concept to explain further the variance in college GPA.

The empirical studies have revealed the significance of high school preparation for academic success in post-secondary institutions. More specifically to mathematical preparation, Buechler (2004) examined the mathematical background of electrical engineering students over a 4-year period. Based on pretest results, he found that a significant number of students did not have the proper mathematical background to be successful in electrical engineering. Consequently, a large portion of instructional time during the course was used for remediation. More than 46% of the students had deficiencies in either algebra or trigonometry. These findings reflected the lack of high school mathematical preparation for quantitative majors.

The results of the Besterfield-Sacre et al. (1997) study suggested that students with adequate mathematical abilities might not be successful in the field of engineering because their self-assessed abilities and confidence level were not equivalent to their actual abilities. For the participants who left engineering in poor standing, they had confidence in their abilities but were not academically prepared, which may be related to their inability to manage time and study course material effectively. In a similar study, Burtner (2004) investigated the relationship between persistence in the engineering curriculum and high school achievement, attitudes, and college academic performance. He concluded that high school GPA indicated the student's ability to persevere and study, which are significant predictors for academic success in college.

Limited research exists for predicting academic success using cognitive and non-cognitive factors (i.e., self-concept, study habits, and inquisitiveness) (House, 1995b, 2000). A study conducted by LeBold and Ward (1988) investigated the cognitive and non-cognitive variables associated with college and engineering retention using a national and institutional sample. In addition to academic background factors, the researchers found self-perceived abilities in math and problem solving were strong predictors of persistence in engineering. House (1995b) reported similar findings with his study to predict achievement in an introductory college mathematics course.

In a study by Blumner and Richards (1997), study habits were found to be associated with academic achievement because participants with high GPAs had significantly lower levels of distractibility and higher levels of inquisitiveness. The research of Shaughnessy, Spray, Moore, and Siegel (1995) connected non-cognitive factors with academic success. They investigated personality factors, SAT scores, and screening test scores to predict the final grade in calculus I for pharmacy majors. While the screening test for calculus was the most significant predictor, three personality factors (reasoning, emotional stability, and privateness) were significant contributors to the model. These results supported the notion that participants who were abstract thinkers tended to be more successful in calculus I than concrete thinkers.

Numerous research studies found cognitive factors, such as academic background and standardized test scores, to be significant predictors of academic success in engineering; however, limited research investigated the relationship between non-cognitive factors and academic success in engineering (French, Immekus, & Oakes, 2005; House, 2000; Shuman et al., 2003). The purpose of this study was to determine if cognitive factors mediate the effect of non-cognitive factors on quantitative GPA and to determine if these cognitive and non-cognitive factors can predict admission status in engineering education.

Research Questions

The study addressed the following research questions:

1. Do cognitive factors (ACT math scores, high school math grades, and high school ranks) mediate the influence of non-cognitive factors on quantitative GPA in the pre-engineering curriculum?

2. Can cognitive and non-cognitive factors predict engineering admission status?

Definition of Terms

<u>Cognitive factors</u> – Academic background factors including standardized test scores, high school ranks, and high school GPAs (House, 2000).

<u>Core curriculum</u> – The requirements for core curriculum differs by engineering major. In general, the following quantitative units are required for each major: 3 calculus, 1 linear algebra, 1 differential equations, 2 chemistry, and 2 physics courses. The humanities requirements are 2 English composition, 2 world literature, and 2 history courses. Other requirements include an orientation to engineering and an introduction to computing courses. The remaining courses taken during the first 2 years of study are major-specific requirements.

Mathematics – A broad field of study encompassing numbers and operations, algebra, geometry, measurement, and data analysis (National Council of Teachers of Mathematics, 2000).

Mathematical problem solving – The ability to apply and generalize various mathematical concepts in order to solve contextual and multiple-step problems (National Council of Teachers of Mathematics, 2000).

Non-cognitive factors - Perceived abilities, personal attitudes, and confidence in mathematical skills (Burtner, 2005).

Quantitative courses – A group of college courses whose conceptual foundation is based in mathematics (Gainen & Willemsen, 1995). The following courses from the pre-engineering curriculum are considered quantitative courses in this study:

1. College Algebra (MA1000)
2. Pre-Calculus Trigonometry (MA1130)
3. Pre-Calculus Algebra Trigonometry (MA1150)
4. Calculus I (MA1610)
5. Honors Calculus I (MA1617)
6. Calculus II (MA1620)
7. Honors Calculus II (MA1627)
8. Calculus for Engineering and Science I (MA1710)
9. Calculus for Engineering and Science II (MA1720)
10. Calculus III (MA2630)
11. Calculus for Engineering and Science III (MA2730)
12. Survey of Chemistry I (CH1010)
13. Survey of Chemistry II (CH1020)
14. Fundamentals of Chemistry I (CH1030)
15. Fundamentals of Chemistry II (CH1040)
16. General Chemistry I (CH1110)
17. Honors General Chemistry I (CH1117)
18. General Chemistry II (CH1120)
19. Honors General Chemistry II (CH1127)
20. Foundations of Physics (PH1000)
21. General Physics I (PH1500)
22. General Physics II (PH1510)
23. Engineering Physics I (PH1600)

24. Honors Physics I (PH1607)
25. Engineering Physics II (PH1610)
26. Honors Physics II (PH1617)

Brief Methodology

The participants in this study were a sample of 2,276 students who entered Auburn University during the fall semester of 2000 through the fall semester of 2004. The participants who had an intended engineering major included 1,857 (81.6%) males and 419 (18.4%) females. Of these cases, the racial classification was 1,885 (82.8%) White, 258 (11.3%) Black, and 133 (5.8%) students who reported that they belonged to other racial groups.

Requirements for participation in this study included completion of the College Freshman Survey (Halpin & Halpin, 1996) and at least two quantitative courses in the pre-engineering curriculum at Auburn University. The final letter grades in each quantitative course were coded using the 4-point scale, A = 4, B = 3, C = 2, D = 1, and F = 0, and were averaged together to create the quantitative GPA.

Exploratory factor analysis. The sample was randomly divided into two databases of comparable size. With one database, an exploratory factor analysis using principal axis factoring with an oblimin rotation was conducted using the following scales from the College Freshman Survey: Math Self-Concept, Self-Appraisal, Perceived Difficulty, Problem-Solving Ability, Need Help, Academic Difficulty, Study Habits, and Academic Self-Concept. The purpose of this factor analysis was to discover the factor structure of the selected items and the correlations between the factors.

Confirmatory factor analysis. With the second database, a confirmatory factor analysis was conducted to determine how the theoretical structure fits with the data and to crossvalidate the factor structures created with the exploratory factor analysis (Meyers, Gamst, & Guarino, 2006).

Structural equation model. After the initial frequencies, descriptives, and bivariate correlations were assessed, a structural equation model was created using AMOS 7.0 to determine the relationship between cognitive and non-cognitive factors and quantitative GPA in the pre-engineering curriculum with 60% of the sample. The exogenous variables were the non-cognitive factors that were created and were confirmed with the factor analyses and the cognitive factors [American College Testing Program (ACT) math score, mean high school math grades, and high school ranks]. Since these data have not been previously analyzed with structural equation modeling, the model created with the 60% sample was applied to the 40% cross-validation sample to confirm the analysis results.

Discriminant function analysis. A discriminant function analysis was conducted using the 60% sample to develop a weighed linear combination to predict group membership (i.e., admitted to engineering, switched to another major at the university, or left the university unsuccessful). The analysis used admission status as the grouping variable and the cognitive and non-cognitive factors as the independent variables. The 40% holdout sample was used to crossvalidate to results with the analyzed 60% sample.

Limitations of Study

The College Freshman Survey: Engineering Form (Halpin & Halpin, 1996) was administered during freshman orientation. Due to the time frame for survey administration, incoming engineering students may have elected to participate in other activities and did not complete the survey. During the academic years used in this study, approximately 71% of the pre-engineering freshmen completed the survey. Another limitation of the study was that the results cannot be generalized due to the use of a single university data source. In addition, this sample included traditional-aged college students who were primarily White males. Furthermore, the effects of background variables, such as socioeconomic status, were not investigated in this study. Lastly, attitudes and self-assessed abilities collected with the College Freshman Survey may change over time and may be affected when students transition from high school to college.

Significance of the Study

To predict academic success in post-secondary education or within a specific curriculum, standardized test scores and high school ranks have been found to be significant predicting variables. The findings of Baron and Norman (1992), Edge and Friedberg (1984), and Smith and Schumacher (2005) indicated that high school ranks were the most significant contributor to academic success. Other researchers (e.g., House, 1995b; House, Keely, & Hurst, 1996; Wilhite, Windham, & Munday, 1998) found that ACT scores were the most significant contributors to academic success and persistence.

In the previous studies, cognitive factors were used to predict academic success, but the results were used to advise and place students within the college curriculum, to restructure the college curriculum and instruction, or to retain the engineering majors. Smith and Schumacher (2005) specifically addressed mathematical preparation (i.e., high school calculus grades), but the predictive model used college students who were enrolled in an actuarial program of study.

Pertaining to the field of engineering, Buechler (2004) and Burtner (2004) investigated college mathematical background with electrical engineering majors. The nature of science, engineering, and mathematics college courses tends to be quantitatively oriented, and calculus tends to serve as the gateway course for academic success within these majors (Gainen & Willemsen, 1995). According to House (1995b), non-cognitive factors significantly contribute to college mathematics achievement beyond standardized test scores or high school ranks. House (1993) examined the effects of non-cognitive factors on academic success after covariating for the effects of the ACT scores and found that students with lower academic self-concepts tended to earn lower grades in college algebra courses.

Numerous studies have examined the relationship between academic success and academic self-concept (Burtner, 2004; Burtner, 2005; House, 1995a, 1995b, 1995c, 2000), math abilities (Burtner, 2004; Burtner, 2005; House, 1995a, 1995c; LeBold & Ward, 1988; Shuman et al., 2003), and problem-solving ability (Besterfield-Sacre et al., 1997; Blumner & Richards, 1997; Brown, 1994; Burtner, 2004; Lackey, Lackey, Grady, & Davis, 2003; LeBold & Ward; Litzinger et al., 2005; Shaughnessy et al., 1995). Fewer studies have investigated the influence of self-awareness (Besterfield-Sacre et al.; Brown; Brown & Cross, 1993; Harackiewicz, Barron, Tauer, & Elliot, 2002; House, 1995b; Shuman et al.) and study habits (Besterfield-Sacre et al.; Blumner & Richards, 1997; Burtner, 2004; Harackiewicz et al.; Nixon & Frost, 1990; Wesley, 1994) on academic success.

Beyond the variables used in these studies, the majority of statistical analyses used with these previous studies were correlational and multiple regression analyses. These predictive and correlational studies accounted for the variance in the cumulative GPAs at the college level, which contain humanities and elective courses. Other studies predicted first semester GPAs (Besterfield-Sacre et al., 1997; Brown, 1994) or final grades in a psychology (Harackiewicz et al., 2002; House et al., 1996), science course sequence (House, 1995a; Sadler & Tai, 2001), and in a calculus sequence (Edge & Friedberg, 1984; House, 1995b, 1995c; Shaughnessy et al., 1995; Wilhite et al., 1998). One study (Smith & Schumacher, 2005) used a multiple regression analysis to predict math GPA with actuarial graduates. A few studies used logistic regression (Besterfield-Sacre et al., 1997; French et al., 2005; House, 1995a; Moller-Wang & Eide, 1997; Zhang et al., 2004) and discriminant analyses (Burtner, 2005; Gilbert, 1960) to predict group membership in mathematics courses or admission status.

Structural equation analyses have not been used to explain the relationship between cognitive and non-cognitive factors and quantitative GPA, more specifically for engineering majors. By using a structural equation model, the relationship between the latent variables can be assessed while controlling for measurement error. In addition, the extent to which the theoretical framework and empirical data are consistent can be determined. Finally, these multiple regression analyses can determine the extent to which the measured variables define the respective latent variables (Meyers et al., 2006).

In addition, previous studies have not addressed the need for developing mathematical problem-solving abilities at the secondary level so the students will be better prepared for the quantitative courses within the rigorous pre-engineering curriculum (Litzinger et al., 2005; Wise, Lee, Litzinger, Marra, & Palmer, 2001; Wulf & Fisher, 2002). According to the National Academy of Engineering (2005), future generations need to be educated to be lifelong learners who are critical thinkers and able to visualize multiple solutions for a given situation. Unfortunately, according to the

NAEP data, the majority of 12th-grade students cannot solve multiple-step word problems despite enrollment in advanced mathematics courses (Campbell et al., 2000).

Considering the limited research that focuses on the predictive relationship between cognitive and non-cognitive factors and academic success in quantitative courses, the need for further research is apparent. Therefore, this research study builds upon and expands the findings of French et al. (2005), House (2000), and Shuman et al. (2003) by investigating the relationship between cognitive and non-cognitive factors and quantitative GPA of incoming freshmen who have indicated they will major in engineering.

Organization of the Study

Chapter I introduces the study, statement of the problem, research questions, and definition of terms. Chapter II includes a review of the current literature considering academic success in undergraduate curriculum and academic success in the engineering curriculum. Chapter III describes the participants, instrumentation, data collection, and data analyses. The results of the statistical analyses are presented in Chapter IV. Chapter V contains summarized findings and future research implications. Chapter VI outlines the contextual information about secondary mathematics, proposed secondary mathematics curriculum, and proposed program evaluation plan.

CHAPTER II

REVIEW OF LITERATURE

The purpose of this study was to determine if cognitive factors mediate the effect of non-cognitive factors on quantitative GPA and to determine if these cognitive and non-cognitive factors can predict admission status in engineering education. To define and investigate the issue, the following external forces pertaining to secondary mathematics and students who enroll as pre-engineering majors were examined: (a) predicting success in the undergraduate curriculum and (b) predicting success in the engineering curriculum. Since there is limited literature that has investigated the relationship between cognitive and non-cognitive factors and success in a pre-engineering curriculum, research in this area requires further examination (French et al., 2005; House, 2000; Shuman et al., 2003).

Predicting Success in the Undergraduate Curriculum

Noble, Roberts, and Sawyer (2006) investigated factors (background characteristics, high school academic achievement, educational accomplishments, and self-perceptions) related to performance on the ACT. The ACT composite score, which ranges from 1 to 36, is an average of the four subject subtests: English, Mathematics, Reading, and Science. The curriculum-based measure was developed to measure knowledge acquired in high school and to measure the skills needed for academic success in post-secondary institutions. The participants for this study were selected by school to maximize within school sample sizes. The sample included high school juniors and seniors who registered to take the ACT in February 2002 (n = 1,906) or in April 2002 (n = 1,400). Two weeks after the ACT administration, participants were mailed a survey to measure non-cognitive factors.

Using structural equation model analyses, the researchers found high school academic achievement (high school mathematics courses, honors or AP courses, and high school GPA in the four core subjects) had a direct effect on the ACT score (R^2 = .63 for African American students and R^2 = .64 for Caucasian American students). Family background (household income, parents' level of education, and number of negative situations present in the home), educational accomplishments (extracurricular activities and out-of-class accomplishments), and psychosocial factors (self-concept, positive attributions, self-efficacy, problem-solving skills, and interpersonal communication skills) had an indirect effect on the ACT score and a direct effect on high school academic achievement (R^2 = .42 for African American students and R^2= .28 for Caucasian American students) . The number of high school mathematics courses completed, number of honors or AP courses completed, and high school GPA had a moderate relationship with the ACT score for both ethnic groups; correlation coefficients ranged from .35 to .56 (Noble et al., 2006).

These results suggest that academic achievement in high school, such as rigorous curriculum and successful grade performance, can increase one's performance on the ACT. Furthermore, according to Noble et al. (2006), the development of non-cognitive factors, such as positive coping skills and realistic self-appraisal of abilities, can assist students in overcoming background factors that might otherwise affect their likelihood of academic success.

Cognitive factors. Standardized tests, such as the ACT and SAT, are examined in various empirical studies in regard to predicting success in the undergraduate curriculum. Other cognitive factors related to cognitive factors include high school GPAs and high school ranks (Edge & Friedberg, 1984; Sadler & Tai, 2001; Smith & Schumacher, 2005; Wilhite et al., 1998).

A study conducted by Edge and Friedberg (1984) investigated the relationship between cognitive factors and academic success in the first calculus course in college. The cognitive variables were ACT scores, high school ranks, high school GPAs, high school algebra grades, and scores from an algebra pretest. Other predictor variables include gender, birth order, family size, and high school size. The participants were three groups of students at Illinois State University. The first group (n = 235) enrolled at the university during the fall of 1976, the second group (n = 157) enrolled during the fall of 1978, and the third group (n = 397) enrolled during the fall of 1980. The researchers found a high correlation between the algebra pretest scores and the final grades in the calculus course.

A stepwise multiple regression analysis was conducted for each group. For the first group, the algebra pretest scores and high school ranks were the significant contributors to the model (R^2 = .524). Similar results occurred with the second group. For the third group, algebra pretest scores, high school GPAs, ACT math scores, and high school ranks were significant contributors to the model (R^2 = .746). Edge and Friedberg (1984) hypothesized that high school ranks represent a measure of competitiveness and long-term characteristic of emotional adjustment; therefore, high school ranks can account for the variance in calculus course grades.

The study by Baron and Norman (1992) confirmed the findings of Edge and Friedberg (1984). The purpose of this study was to predict cumulative college GPAs using high school ranks, SAT scores, and average achievement test scores as predicting variables. The sample included 4,170 freshman students who enrolled at the University of Pennsylvania during the fall terms of 1983 and 1984. Of these participants, 2,781 were in the field of arts and sciences, 647 in business, 585 in engineering, and 157 in nursing. A multiple regression analysis was conducted to predict cumulative college GPAs. High school ranks was the best single predictor in the model ($R^2 = .093$). When high school ranks were combined with College Board Achievement Tests, the model accounted for 13.6% of the observed variance in the college GPA. SAT scores were found to have a small contribution to the overall prediction model.

A study conducted by Burton (1989) examined 741 students who took the final exam in a calculus I course. The participants were asked to describe their high school preparation for calculus on a continuum from no previous experience to a full year in an AP calculus course. Burton conducted frequency and descriptive counts to analyze his data. He found 56.5% of the participants who reported minimal or no experience made Ds and Fs as final course grades. For the students who reported they had had one full year of calculus experience, 16.6% of the participants made a D or F as a final course grade. Furthermore, Burton reported that previous high school calculus experience may not be sufficient for the participant to exempt the college introductory calculus course. These results suggest that success in calculus I was heavily dependent on the participant's high school experience.

To explain further the variance within calculus grades, Wilhite et al. (1998) investigated the effects of high school calculus and academic achievement variables on the undergraduate achievement in calculus I. The participants were selected as a stratified random sample from 1,542 calculus I students at the University of Arkansas. Of the 182 selected participants, a stepwise multiple regression was conducted to predict the final grade in calculus I. The researchers explained 29.9% of the variance in the calculus I final grade. The most significant predictor was ACT math scores followed by high school ranks, ages, and high school mathematics GPA. High school calculus background had a low positive correlation with the dependent variable and was not significant in the regression model. The researchers suggest that high school calculus be taught to students who intend to earn college credit concurrently; however, to accomplish this goal, the mathematics curriculum needs to be restructured to include the skills to master college-level calculus.

Murtaugh, Burns, and Schuster (1999) investigated the cognitive factors associated with student retention at Oregon State University. The participants in this study were 8,867 undergraduate students who enrolled during the fall quarters of 1991 through 1995. Predictor variables included demographic variables (gender, ethnicity, residency, college, and age at first enrollment) and academic characteristics (high school GPAs, SAT scores, and first quarter college GPAs), and involvement (participation in educational program and freshman orientation).

With the Kaplan-Meier method, a series of univariate analyses was conducted to provide a nonparametric estimate of retention probability over time: 1, 2, and 4 years. For participants with a high school GPA between 3.3 and 4.0, after 1 year, their estimated retention rate was 86.2%. That percentage decreased to 68.9 after 4 years. On the other hand, for the participants with a high school GPA between 2.0 and 2.7, their estimated retention rate was 65.9% after 1 year, and it decreased to 35% after 4 years. First quarter GPA had similar percentages. The participants with a first quarter GPA between 2.7 and 3.3 had an estimated retention rate of 87.6% after 1 year, and it decreased to 65.9% after 4 years. When the participants had a first quarter GPA less than 2.0, their estimated retention rate was 57.2%, and it decreased to 33% after 4 years (Murtaugh et al., 1999).

A stepwise regression model was developed using the Cox proportional hazards regression model. Significant contributing variables were first quarter GPA, freshman orientation, high school GPA, residency, college, ethnicity, and age. The results of the univariate and multivariate analyses indicated the strong association between student retention and high school and first quarter academic performance. The researchers noted that high school GPA surpassed the SAT score as a predictor of student retention (Murtaugh et al., 1999).

Sadler and Tai (2001) investigated demographic and high school background factors to account for the variance in the grades in an introductory college physics courses. The participants were 1,933 from 18 colleges and universities (9 public state institutions, 8 private institutions, and 1 military academy). A multiple regression analysis was conducted to predict the college grade in introductory physics. The resulting model accounted for 25.8% of the variance in the college grade.

Significant predicting variables were type and location of high school, ethnicity, parent's level of education, high school GPA, high school courses in calculus and physics, college year, and professor's gender being the same as the student's gender. Variables, which were not statistically significant and excluded from the model, were class climate (i.e., instructional practices), problem solving (i.e., quantitative problems presented during class), school issues (i.e., high school size), student decisions (i.e., high school courses in chemistry and biology), teacher attributes (i.e., pedagogy), labs and project work (i.e., student participation in science fairs), and gender. Sadler and Tai (2001) noted that some participants may tend to avoid more rigorous coursework in high school in order to avoid a negative impact on their high school GPA, but exposure to high school calculus can increase the likelihood of success in college physics courses (Sadler & Tai, 2001).

Smith and Schumacher (2005) examined predicting variables for success in undergraduate mathematics courses. The participants in this study were 106 actuarial graduates from Bryant College from 1996 to 2003 and 776 freshman students who entered during the 2003 academic year. A multiple regression was conducted to predict the overall math GPAs using the SAT quantitative scores, SAT verbal scores, high school ranks, and the college's mathematics placement scores. The model was significant with a R^2 of .454. All variables were significant contributors to the model; however, high school ranks were the most significant.

Another purpose of this study was to predict the post-calculus GPA. A multiple regression analysis was conducted using the same independent variables with the addition of the average of the two calculus courses. The restricted model, with high school ranks and calculus grades, accounted for 57.9% of the variance after the two-course sequence of calculus was completed. These results suggest that college calculus is a significant predictor for academic success in college. The researchers suggested the additional research for mathematical ability, interest, study habits, and academic self-concept to explain further the variance in college GPA (Smith & Schumacher, 2005).

In summary, researchers found standardized test scores, high school ranks, and high school GPAs were significant predictors of academic success in the undergraduate curriculum. These predictors accounted for the variance in retention probability (Murtaugh et al., 1999), college calculus courses (Burton, 1989; Edge & Friedberg, 1984; Smith & Schumacher, 2005; Wilhite et al., 1998), introductory college physics courses (Sadler & Tai, 2001), and cumulate college GPAs (Baron & Norman, 1992).

Non-cognitive factors. The vast amount of empirical research that predicts success in post-secondary institutions involves cognitive factors. A few studies exist that use non-cognitive factors, such as personality traits and attitudes, to predict academic success. College admission officers want to quantify the individual differences (e.g., study habits and academic self-concepts) among undergraduate students and use these differences to account for the variation of college GPAs (Nixon & Frost, 1990; Wesley, 1994).

Nixon and Frost (1990) developed a 37-item inventory to measure study habits and attitudes about overall academic ability. Using this instrument, the researchers examined the study habits and attitudes of 128 undergraduate and graduate students to predict their cumulative college GPAs. The researchers found those participants who scored lower on the inventory tended to have higher GPAs, but the *t* tests were not statistically significant.

There was a significant correlation between academic goals and college GPAs ($r = .58$; $p < .001$). Likewise, there was a significant correlation between academic self-concept and college GPAs ($r = .56$; $p < .001$). Both of these relationships suggested that participants who were goal-oriented and had high academic self-concepts tended to have higher GPAs than those participants with lower self-concepts and who lacked goal-setting ability. Those participants who reported moderate levels of study time tended to have higher GPAs compared to those participants who reported high or low levels of study time. These results suggested that increased study time can lead to higher GPAs, but a curvilinear relationship existed between grades and study time which means more study time may indicate poor study skills or lack of ability (Nixon & Frost, 1990).

Shaughnessy et al. (1995) used the 16 Personality Factor Questionnaire to assess 87 pharmacy majors. In addition to the personality factors, the researchers collected SAT scores and screening test scores for algebra and calculus. A multiple regression analysis was conducted to predict the final grade in calculus I. The screening test for calculus was the most significant predictor; however, three personality factors (i.e., reasoning, emotional stability, and privateness) were significant contributors to the model. The model accounted for 28% of the variance in calculus I grades. These results suggest individuals who are abstract thinkers tend to be more successful in calculus I than concrete thinkers.

Another study conducted by House (1995c) examined 218 freshmen at a large U.S. university. Prior to their first semester at the university, the participants were given an attitude questionnaire. The purpose of this study was to determine the predictive relationship between the participants' attitudes and achievement in their first college calculus course. More specifically, the attitudes that were examined in this study were (a) overall academic ability, (b) mathematics ability, (c) drive to achieve, and (d) intellectual ability. Using a multiple regression analysis, he found overall academic ability and mathematical ability to be the most significant predictors, which accounted for 13.4% of the variance in the calculus grades.

In summary, researchers (House, 1995c; Nixon & Frost, 1990; Shaughnessy et al., 1995) found academic self-concept, academic goals, reasoning, academic ability, and mathematical ability to be significant contributors for academic success in the undergraduate curriculum. These predictors accounted for the variance in a college calculus courses and cumulative college GPAs.

Cognitive and non-cognitive factors. As the interest in non-cognitive factors has increased, the interest in the relationship between cognitive and non-cognitive factors and academic success has increased. A number of non-cognitive factors have been identified by empirical findings, such as interests and attitudes. Several of these factors have been found to have a significant relationship with academic achievement at the post-secondary level. Further research is needed to investigate the effects of cognitive and non-cognitive factors on academic success in undergraduate curriculum (House, 1995a).

House (1993) examined the relationship between achievement-related expectancies, academic self-concept, and mathematical performance with students who were admitted to the university through academic services program for students who lack the college-preparatory course sequence. The participants were first-generation college students from low socioeconomic backgrounds. Academic expectations and self-concept were measured with a survey, which was administered during an orientation session prior to enrollment. The independent variables were gender, ethnic group, achievement expectations, and academic self-concept, and the dependent variable was the final grade in college algebra.

An analysis of covariance (ANCOVA) was conducted with ACT composite scores as the covariate. The main effect of academic self-concept was significant, $F(1, 178) = 5.65$; $p < .05$, and Duncan's multiple range procedure revealed students with lower self-concepts earned significantly lower grades in the college algebra course. The main effect for gender was also significant, $F(1, 178) = 4.90$; $p < .05$, and follow-up procedures revealed that females earned statistically significant higher grades. Achievement, $F(1,178) = 3.79$; $p < .10$, and ethnic group, $F(1, 178) = 3.08$; $p < .10$, were not statistically significant nor were the two-way interaction effects for the variables (House, 1993).

These results indicated that academic self-concept was related to mathematical ability for students who lack college preparation, and, with this sample, the underprepared students may have graduated from secondary school with an unrealistic self-concept of their abilities and an unrealistic understanding of the demands in post-secondary institutions. A limitation of this study may be the use of course grades as the dependent variable because grades can be affected by effort and persistence with classroom assignments as well as mathematical ability (House, 1993).

Wesley (1994) examined ability, high school achievement, and procrastinatory behavior as predictors of cumulative college GPAs with 244 undergraduate students enrolled in a psychology course. Procrastinatory behavior was measured with the 10-item Self-Handicapping Scale and the 5-item Procrastination Assessment Scale. The cognitive factors were achievement (high school grade averages and GPAs) and ability (SAT scores). A series of stepwise multiple regression analyses were conducted by gender. The significant contributing variables were high school averages, procrastination, and SAT scores for the male (R^2 = .50) and female models (R^2 = .29). The results of this study suggest procrastination accounts for a significant portion of the observed variance in cumulative GPAs beyond SAT scores and high school grade averages.

House (1995a) investigated the predictive relationship between initial student attitudes, standardized admission test scores, high school curriculum, and grade performance in an introductory college chemistry course. The participants included a sample of 179 freshman students with a mean age of 18.11 years. During an on-campus orientation session, all participants completed a survey to measure academic abilities and expectations of academic success. Multiple regression analyses were conducted with the following predictor variables: (a) overall academic ability; (b) mathematics ability; (c) drive to achieve; (d) intellectual ability; (e) ACT composite scores; and (f) number of high school mathematics courses completed. All predictor variables were significantly correlated with the dependent variable, grade performance in the chemistry course.

The results of the stepwise multiple regression analysis revealed self-ratings of mathematical ability and overall academic ability as statistically significant contributors to the model (R^2 = .23). A cross-validation analysis was conducted using cognitive and non-cognitive factors to examine the consistency of ordering the predictor variables. This analysis revealed mathematical ability and ACT composite scores as the statistically significant contributors to the model (R^2 = .31) (House, 1995a).

A logistic regression analysis was conducted to investigate the relationship between the cognitive and non-cognitive factors and passing the introductory college chemistry course (final grade of A, B, or C). The only statistically significant contributor was mathematical ability. The results of this study suggest initial attitudes (e.g., self-ratings of mathematical ability) are better predictors of academic success than ACT composite scores or number of high school mathematics courses completed (House, 1995a).

House (1995b) further investigated the relationship between cognitive and non-cognitive factors with his study of academic success in introductory college mathematics courses. This sample included 958 freshman students. As in the previous study, House administered a survey to the participants during an on-campus orientation session. Multiple regression analyses were conducted with the following predictor variables: (a) overall academic ability; (b) mathematical ability; (c) drive to achieve; (d) intellectual ability; (e) ACT composite scores; and (f) number of high school mathematics courses completed. Four of the six predictor variables were statistically significant contributors to the model: mathematical ability, overall academic ability, intellectual ability, and ACT composite scores (R^2 = .12).

As a follow-up, a stepwise logistic regression analysis was conducted to determine the relationship between each cognitive and non-cognitive factor, respectively, and satisfactorily passing the college mathematics course. The significant contributing predicting variables were mathematical ability, drive to achieve, and ACT composite scores. These results suggest that self-ratings of mathematical ability are the most significant predictor variable of academic success in mathematics courses. The number of high school mathematics courses completed was not a significant contributor; however, House (1995b) noted the enrollment in more high school courses may increase the students' self-confidence in their mathematical ability.

A study conducted by House et al. (1996) examined the relationship between initial attitudes, prior achievement, and academic achievement in a general college psychology course. The participants were 335 students, with 102 of them from a private urban university and 233 from a rural public university. At an orientation session prior to fall semester, each participant completed an attitudinal survey. After conducting bivariate correlations, multiple regression analyses were conducted with the same predictor variables used in the previous House studies (1995a, 1995b, 1995c).

Mathematical ability and overall academic ability were highly correlated with the number of high school mathematics courses completed for both universities. Moreover, all non-cognitive factors and the number of high school mathematics courses completed were highly correlated with the ACT composite scores. In the regression model, ACT composite scores and the number of high school mathematics courses completed were the two statistically significant predictor variables. With a stepwise logistic regression analysis to determine the relationship between the predictor variables and earning a satisfactory course grade, ACT composite scores were the only statistically significant contributor for both universities (House et al., 1996).

Harackiewicz et al. (2002) investigated the relationship between cognitive and non-cognitive factors and students' interest and performance in an introductory psychology course. The participants were 471 freshman and sophomore students who were enrolled in an introductory psychology course. The predictor variables were

ACT/SAT scores, high school ranks, achievement motivation (as measured by the Work and Family Orientation Questionnaire), and interests and goals in psychology (as measured by a self-reported questionnaire). The dependent variables were the final course grade and semester GPA.

A series of multiple regression analyses were conducted using the predictor and dependent variables. The model predicting the final course grade had a R^2 of .34. The significant contributors were performance-approach goals, work avoidance goals, ACT/SAT scores, high school ranks, instructor, and gender. The results suggest that participants who displayed work avoidance goals tended to have lower course grades. Those participants who had higher ACT/SAT scores, performance-approach goals (i.e., competitiveness and workmastery), and high school ranks tended to earn higher course grades (Harackiewicz et al., 2002).

In summary, several researchers have investigated the relationship between cognitive and non-cognitive factors and the undergraduate curriculum. For example, Wesley (1994) found cognitive and non-cognitive factors accounted for the variance in cumulative college GPAs. Similarly, Harackiewicz et al. (2002), House (1995a, 1995b), and House et al. (1996) investigated predictors of academic success in introductory psychology, chemistry, and college mathematics courses. Their findings revealed mathematical ability, overall academic ability, and academic self-concept to be significant predictors of academic success in the undergraduate curriculum in addition to standardized test scores and high school GPAs.

Predicting Success in Engineering Curriculum

Cognitive factors. Mathematical ability serves as a foundation for the quantitative-oriented curriculums, and it is considered a critical factor for achieving success in engineering. In addition, mathematical problem-solving skills are necessary for solving engineering problems (Heinze et al., 2003). Historically, standardized test scores and other cognitive factors have been linked by researchers to academic success in engineering (Lackey et al., 2003).

Gilbert (1960) conducted a study to determine the effectiveness of College Entrance Examination Board exams (i.e., SAT, Advanced Mathematics test, and Science test) to predict graduation from the School of Engineering at Princeton University. The participants in this study were 123 students who entered the university during the fall of 1953. A discriminant analysis technique was conducted to predict group membership. Gilbert did not find a statistically significant difference between the mean scores for the attrition and survival groups. The results suggest that standardized test scores cannot be used as the single predictor of success in engineering. Therefore, factors other than academic aptitude should be examined to predict graduation in engineering.

Moller-Wong and Eide (1997) conducted a study to determine why engineering students stayed and why they chose to leave the major at the College of Engineering at Iowa State University. A cohort of 1,151 students who entered in the fall of 1990 was selected as participants for this study. A backward elimination logistic regression analysis was conducted to predict higher or lower risks of attrition (i.e., graduation from engineering, changed to another major in good standing, left the university, and still enrolled) with a possible 100 predicting variables.

Moller-Wong and Eide (1997) found marital status, ethnic classification, ACT composite scores, number of semesters in English while in high school, and number of semesters in art while in high school were significant predicting variables for the participants who left the university. For the participants who successfully graduated from engineering, the number of transfer credits, residency status, high school ranks, ACT math scores, number of semesters in physics while in high school, and number of semesters in social science while in high school were significant predicting variables. The logistic regression model was able to classify correctly 81% of the successful graduates and 75% of the participants who left the university.

In a correlational study, van Alphen and Katz (2001) investigated the relationship between college GPAs, grades in prerequisite classes, scores on prerequisite assessment quizzes, and math readiness as measured by math placement exams. Another significant indicator of success for freshmen included high school GPAs. The researchers found that SAT quantitative scores were not significantly correlated with success in electrical engineering. The study included 229 participants from California State University who completed the Electrical Engineering Fundamentals course over a 2-year period.

Conversely, Devens and Walker (2001) conducted a study using SAT scores and baseline math tests to predict success in a first semester engineering course. The participants in this study were 3,087 freshman engineering students from fall 1997 through spring 1999. The researchers found a correlation of 50 SAT points for every 1.0 increase in the course grade. Furthermore, students with SAT scores greater than 1300 were more likely to pass the course compared to those students with SAT scores less than 1000. The researchers recommended that in future studies SAT quantitative and verbal scores should be examined separately to predict student performance in the first semester courses.

Heinze et al. (2003) collected 6 years of data at Texas Tech University using over 4,000 students. The researchers analyzed the data to determine student success in sequential mathematics courses. After initial placement according to previous college math courses or the results of the math placement exams, the researchers found that the majority of the students began the sequence at calculus I. The students who began the sequence at calculus II had an 85% success rate through calculus III; however, those students who began the sequence at college algebra had a 25% success rate through calculus III. Their results suggest that the math placement could serve as a predictor of academic success in engineering. As noted by Heinze et al., the math placement exam in this study was administered to the students after their admission to the university. Therefore, the quantitative section of the SAT could be a predictor of success in engineering because it is an assessment tool for algebra and below.

Burtner (2004) examined the mathematical background of 142 students who graduate in electrical engineering. Of these 142 participants, 82 completed their calculus sequence at the university. Frequencies and descriptives were assessed for GPA and initial math placement. According to their math placement test, 43.9% of the entering freshmen were calculus ready, and 24.4% of the freshmen began their math sequence in intermediate algebra or below. Final grade in the first semester of calculus was found to be an indicator of student performance in the engineering curriculum. Furthermore, for those students who were poorly prepared for the mathematics curriculum, if they were successfully placed within the sequence and understood the content, they tended to be successful in the calculus sequence.

Buechler (2004) examined the mathematical background of students who graduated from University of Wisconsin-Milwaukee with a degree in electrical engineering over a 4-year period. Based on pretest results, he found that a significant number of students did not have the proper mathematical background to be successful in electrical engineering. Therefore, a large portion of the coursework had to be used for reviewing prerequisite material. Using the transcripts of 142 students, the researcher conducted analyses using the degree GPA, calculus sequence GPA, and electrical engineering core course GPA. He found that 43.9% of the graduates were calculus ready when they entered the university. More than 46% of the students had deficiencies in either algebra or trigonometry. Students who began their calculus sequence with trigonometry had the highest GPA in all three categories, which indicated a higher success rate for those students, but students who received a C or better in calculus I were more likely to be successful in the electrical engineering core curriculum. Moreover, Buechler noted indicators for future success were ACT math scores, SAT quantitative scores, high school GPAs, and high school ranks. A significant number of students had to retake more than one mathematics course, and these students tended to have lower GPAs.

Zhang et al. (2004) examined 15 years of student data across nine universities. The purpose of the study was to determine the demographic and academic factors upon graduation for engineering students. The participants were 47,065 freshmen from eight schools of engineering. A logistic regression model was conducted using six predicting variables (i.e., ethnicity, gender, citizenship status, high school GPAs, SAT quantitative scores, and SAT verbal scores) to predict graduation in engineering. The researchers found that high school GPAs and SAT quantitative scores were positively correlated with graduation across all universities. The coefficient of determination indicated that the predicting variables accounted for a significant and meaningful variation in graduation (R^2 = .126), which indicates there are other pre-existing variables that would account for the variance.

In summary, empirical findings (Buechler, 2004; Burtner, 2004; Devens & Walker, 2001; Gilbert, 1960; Heinze et al., 2003; Moller-Wong & Eide, 1997; van Alphen & Katz, 2001; Zhang et al., 2004) identified cognitive factors as significant predictors of academic success in engineering. More specifically, standardized test scores, high school GPAs, and high school coursework were found to be significant contributors to retention within engineering majors. Future research suggested from these empirical studies the inclusion of quantitative scores from standardized tests and high school ranks.

Non-cognitive factors. The previous research demonstrated the significant contribution of cognitive factors to academic success in engineering; however, some researchers (e.g., Brown & Cross, 1993; Lackey et al., 2003) have found empirical support for the validity of non-cognitive factors and their contribution to academic success in engineering.

Brown and Cross (1993) compared the personality profile of freshman engineering students (*n* = 129) to students who had persisted in the engineering majors (*n* = 85) at Old Dominion University. The Adjective Checklist was used to assess personality of the participants. A series of analysis of variance procedures was conducted to compare the two groups. Statistically significant differences by group were found for achievement, dominance, endurance, abasement, and nurturing parent scales. The results of this study suggest personality can play a vital role in retention of engineering students. Furthermore, if the characteristics of previously retained students differ greatly from the incoming freshmen, then the existing structure may not be effective with the incoming freshmen class and should be revised to meet their needs.

Blumner and Richards (1997) wanted to determine if students who earned higher grades tended to have low levels of distractibility and high levels of inquisitiveness. From a required introductory course in engineering at the University of Virginia, 27 women and 42 men were selected as participants for this study. The Inventory of Study Habits was used to measure study habits. The 18-item survey assessed distractibility, compulsiveness, and inquisitiveness. Other independent variables included SAT verbal scores, SAT quantitative scores, and first-year college GPAs. Multiple regression was conducted to predict GPA. SAT verbal and quantitative scores accounted for 18% of the variance in the GPA. When the study habits were added to the model, the R^2 increased to .33.

Based on the median of the GPAs, the continuous variable was dichotomized into high and low GPAs. Multivariate analyses of variance (MANOVA) were conducted with high and low GPAs and the inventory scales. The results were significant, which means that study habits were associated with achievement. Participants with high GPAs had significantly lower levels of distractibility and higher levels of inquisitiveness. The researchers suggested the promotion of strategies through the curriculum for students who reported low levels of inquisitiveness (Blumner & Richards, 1997).

Lackey et al. (2003) conducted a predictive study with freshman engineering students to determine the effectiveness of a critical thinking notebook on predicting academic success (i.e., GPA after first two college semesters). The participants in this study were 109 students who were enrolled in an engineering professional practices course at Mercer University. Based on the admission criterion, the researchers assumed that all participants were academically prepared in their K-12 curriculum for success in engineering. The predicting variables were SAT combined scores, SAT verbal scores, SAT quantitative scores, high school GPAs, and the grade for the critical thinking notebook. With the critical thinking notebook, the participants took notes in class and reflected upon their learning throughout the semester.

Using a stepwise multiple regression model, the researchers found that SAT quantitative scores, high school GPAs, and the critical thinking notebook were significant predicting variables for college GPA. These variables accounted for 60.3% of the variance in college GPA. The critical thinking notebook accounted for 33.4% of the variance. These results suggested that the grade for the critical thinking notebook measures adequate study habits and problem-solving skills. Therefore, variables representing both ability and interest were the best predictors for college GPA (Lackey et al., 2003).

Litzinger et al. (2005) examined the trends in self-directed learning across the undergraduate years. The participants were randomly selected from all of the engineering majors at Pennsylvania State University. The researchers used two Likert-type survey instruments: Self-Directed Learning Readiness Scale and Continuing Learning Inventory. The results from the analysis of variance revealed a significant difference in self-directed learning across the academic years in college. A Tukey-Kramer pairwise comparison revealed significant differences between the first and second year and the first and fifth year in college. The researchers hypothesized that the differences could be contributed to the presence of more open-ended questions in the classroom. Using a regression analysis to predict the score from the Self-Directed Learning Readiness Scale, the researchers found that academic year and GPA were significant predicting variables..

Another purpose of this study was to investigate the effect of problem-based learning on the Self-Directed Learning Readiness Scale. The survey was administered as a pretest and posttest to the participants in a two-course sequence in industrial and manufacturing engineering. Of the 18 participants, nine participants increased their self-directed learning scores. The problem-based learning used in the course increased the mean self-directed learning score. The results suggested that students needed to be exposed to multiple problem-solving experiences that occurred within a real-world context. By modifying the curriculum, the researchers hypothesized that the students would be able to improve their critical thinking skills (Litzinger et al., 2005).

Burtner (2005) identified non-cognitive factors that influence the persistence of students to remain in the engineering curriculum. To measure the non-cognitive factors, the researcher used the Pittsburgh Freshman Engineering Attitudes Survey. Using discriminant analysis to predict group membership (i.e., stay, switch, or leave) after 1 year of college, Burtner found job security, engineering characteristics, communication skills, and basic math, science, and technology skills significantly differentiated the three groups. The classification percentage was 85.2%. To predict group membership after 3 years of college, another discriminant analysis was conducted using the same four independent variables. Again, the analysis significantly differentiated the groups. In the sample, 76.5% were correctly classified. These results suggest that mathematics and science abilities of engineering students may influence their decision to leave engineering.

In summary, despite the use of cognitive factors as predictors of academic success, success in the engineering curriculum is dependent upon the attitudes that the students bring with them to college (Lackey et al., 2003). These students may have been academically successful in high school, but they may lack the confidence in their mathematical ability. By measuring these initial attitudes, academic success can be achieved (Besterfield-Sacre et al., 1997).

Cognitive and non-cognitive factors. Cognitive factors have the strongest relationship with academic success in engineering fields (Brown, 1994); however, success has been linked to non-cognitive factors as well (Lackey et al., 2003).

LeBold and Ward (1988) investigated the cognitive and non-cognitive variables associated with college and engineering retention with a national and institutional sample. The participants began their studies during 1980 and 1981 at 20 different engineering institutions. The researchers found that the strongest predictors associated with retention in engineering were math ability, high school math grades, SAT quantitative scores, and first semester GPAs. Self-perceived abilities in math, science, and problem solving were strong predictors of engineering persistence.

With the institutional sample at Purdue University, the researchers conducted a bivariate correlation to determine the relationship between the pre-college variables and engineering retention after six semesters. They found that SAT quantitative scores

($r = .22$), high school math grades ($r = .24$), and high school science grades ($r = .21$) had moderate relationships with engineering retention. Grades in the following high school classes had a moderate relationship with engineering retention: trigonometry ($r = .25$), calculus ($r = .24$), chemistry ($r = .24$), and physics ($r = .27$). When the bivariate correlation was conducted with first semester GPAs, a strong relationship existed with all of the previous pre-college variables and high school ranks ($r = .40$) (LeBold & Ward, 1988).

Felder et al. (1993) examined attitudes and expectations of 124 undergraduate students enrolled in an introductory chemical engineering course. The collected data were correlated with the final grade in the engineering course. Statistically significant differences were found with students who had a high academic self-concept ($p < .001$), students who felt they lacked in academic ability and had poor study habits ($p < .01$), and students who reported low levels of distractibility ($p < .05$). For students who reported better than average high school preparation, 80% of them passed the course with a C average or higher ($p < .05$). Moreover, grades in the first-year quantitative courses (calculus, chemistry, and physics) were highly correlated (from .47 to .62) with academic success in the engineering course. These results suggest that the likelihood of passing the introductory course to chemical engineering depended upon high quantitative ability and academic self-concept and low distractibility.

Brown (1994) investigated cognitive and non-cognitive factors to predict the first semester GPAs for 124 freshman engineering students. The participants were administered the College Major Interest Indicator (to identify educational interests), Adjective Checklist (to measure personality traits), Ship Destination Test (to measure symbolic reasoning), and Logical Reasoning Test (to measure verbal reasoning). In addition to these non-cognitive factors, the participants' SAT verbal and quantitative scores were used as predictor variables.

A multiple regression analysis was conducted to predict the first semester GPA. When the 37 scales of the Adjective Checklist were the only predictor variable, the model accounted for 60% of the variance in the first semester GPA. When all cognitive and non-cognitive factors were entered into the model, the model accounted for 66% of the variance in first semester GPA. The researcher noted that cognitive variables may not be as important for predicting academic success when the sample has been screened and admitted to a post-secondary institution on the basis of the cognitive factors, such as high school transcript and standardized test scores. Thus, non-cognitive factors can play a large role in predicting academic success (Brown, 1994).

Besterfield-Sacre et al. (1997) conducted a predictive study for attrition and performance in a freshman engineering program with 417 college freshmen who entered the University of Pittsburgh during the fall of 1993 and 1994. The participants were asked to rate (a) their opinion about the engineering profession and the reasons why they selected engineering as a major, (b) their confidence in the prerequisite knowledge and skills and their abilities to be successful in engineering, and (c) their study skills and their interest to work in groups using the 50-item Pittsburgh Freshman Engineering Survey. The participants rated the attitudinal statements with a 5-point Likert-type scale (i.e., *Strongly Disagree* to *Strongly Agree*) and the confidence statements with a 5-point Likert-type scale (i.e., *Not Strongly Confident* to *Strongly Confident*).

Using the Mann-Whitney non-parametric test, the researchers found that the participants who left engineering in good standing had a significantly lower general impression of engineering and perception of the engineering profession. Likewise, this group of participants who left engineering in good standing had a significantly lower confidence level for the basic engineering knowledge and skills (e.g., problem-solving and creative thinking skills). They also reported significantly lower levels of enjoyment in mathematics and science courses. These results suggested that students with adequate mathematical abilities may not be successful in the field of engineering because their self-assessed abilities and confidence levels were not equivalent to their actual abilities. The participants who left engineering in poor standing had the confidence in their abilities but were not academically prepared. The researchers suggested that this incompatibility may be related to poor time management skills and ineffective study habits (Besterfield-Sacre et al., 1997).

Using a multiple linear regression (stepwise) analysis with fall quarter GPA as the dependent variable, the researchers found that 8 out of 20 possible predictor variables were significant contributors to the regression model, which resulted in a R^2 of .29. Those significant predicting variables were received at least one scholarship, high school ranks, SAT quantitative scores, adequate study habits, enjoyment of math/science, and financial influences for studying engineering (Besterfield-Sacre et al., 1997).

The researchers used a stepwise logistic regression analysis to predict freshman engineering students who would leave in poor standing. They found that SAT quantitative scores, high school ranks, involvement in the freshman academic support program, and financial influences for studying engineering were significant contributors to the model; however, the predicting percentage was 15%. Another logistic regression analysis was conducted to predict the participants who would leave in good standing. High school ranks, general impression of engineering, enjoyment of math/science, and family influences to study engineering were significant contributors to the model (Besterfield-Sacre et al., 1997).

A third logistic regression was developed to predict participants who would leave in good standing, but the researchers only included the attitude and self-assessment measures. In this model, general impression of engineering, enjoyment of math/science, confidence in basic engineering knowledge, and confidence in communication skills were significant predictor variables. The overall predicting percentage for the logistic regression model was 50%. The researchers found that the participants reported a lack of confidence in their abilities and a lower level of interest in math and science. Furthermore, these participants tended to have lower impression of the field of engineering. Besterfield-Sacre et al. (1997) suggested an introduction of more real-world applications into the classroom and the opportunities for the students to participate in field experiences so they can understand the job specifics for a variety of engineering jobs.

House (2000) examined the predictive relationship between achievement in science, engineering, and mathematics curriculums, academic background, and non-cognitive factors. The participants were 658 freshman students over four consecutive fall semesters who indicated an initial science, engineering, or mathematics major. The participants completed the Cooperative Institutional Research Program Annual Freshman Survey during an on-campus orientation session. Based on the data collected from the survey, seven variables were created: (a) achievement expectancies; (b) academic self-concept; (c) financial goals; (d) social goals; (e) desire for recognition; (f) parental education; and (g) high school curriculum. ACT composite scores, high school ranks, and cumulative college GPAs after 1 year were collected.

Two multiple regression analyses were conducted to predict the cumulative college GPA. The first model was created using only the non-cognitive factors. Academic self-concept and financial goals were significant contributors to the model (R^2 = .12). Those participants with higher GPAs reported higher levels of academic self-concept and the participants with lower GPAs reported higher levels of financial goals. The second model was created using the academic background and non-cognitive variables. In addition to academic self-concept and financial goals, high school ranks and ACT composite scores were significant contributors to the model (R^2 = .29). House (2000) suggested further research to assess the joint relationship between academic background variables and non-cognitive factors as predictors of academic success for students who major in science, engineering, and mathematics.

Burtner (2004) investigated the relationship between persistence in the engineering curriculum and high school achievement, attitudes, and college academic performance. The participants were 116 freshman students at Mercer University. Of the cognitive skills, there were significant group differences for retention status for high school GPA and college performance during the first year. The Pittsburgh Freshman Engineering Attitudes Survey was used to assess attitudes. Using ANOVA, the researcher found that enjoyment of engineering, job security, problem-solving abilities, basic skills, and study habits were significant. Burtner hypothesized that high school GPA indicated the participant's ability to persevere and study, which are significant predictors for academic success in college.

Shuman et al. (2003) used the Cooperative Institutional Research Program and the Pittsburgh Freshman Attitudes Survey to determine the self-assessed abilities and predict academic success in the calculus sequences for 394 freshmen who entered the University of Pittsburgh in 2002. Descriptives and frequencies revealed that 17.2% reported needing remediation in mathematics. However, after a follow-up with the tutoring records, approximately half of the students who indicated that they needed remedial studies did not attend tutoring sessions. Of the 394 freshmen, 32.7% reported that their mathematics abilities were among the top 10%. Using a crosstabulation, the researchers found that 87.5% of the participants indicated that they had had high school calculus. Of those students, their calculus grades were at least one letter grade higher than those participants who did not report taking high school calculus. Another crosstabulation revealed students with higher SAT quantitative scores tended to perform better in calculus I.

A Learning Vector Quantization neutral network model was developed to predict initial math placement in the calculus sequence. The predictor variables were gender, high school ranks, SAT scores, placement exam results, attitudes toward mathematics, and background in differential calculus. The model correctly classified 89.5% (Shuman et al., 2003).

French et al. (2005) examined the cognitive and non-cognitive variables that predict success and persistence in engineering. The participants for this study were two cohorts of engineering undergraduate students from a large U.S. midwestern university. The independent variables included gender, participation in orientation class, high school ranks, SAT verbal and quantitative scores, motivation as measured by the Academic Intrinsic Motivation Scale, and institutional integration as measured by the Institutional Integration Scale. Three regression models were conducted: hierarchical multiple linear regression for predicting GPAs and hierarchical logistic regressions to predict university enrollment and major enrollment with GPA as the control variable. The independent variables were entered in the following order: (a) background, (b) motivation and integration, and (c) participation in the orientation class.

In the regression model for predicting GPAs, SAT verbal scores, SAT quantitative scores, high school ranks, and gender were significant contributing variables. These variables accounted for 18% of the variance in GPA. For the logistic regression model for predicting university enrollment, GPA was the only significant contributing variable. The remaining variables did not significantly contribute to the model beyond GPA. The correct classification rate was 89%. To predict major enrollment, the significant contributing variables were GPAs, SAT verbal scores, SAT quantitative scores, high school ranks, and motivation. The overall classification rate was 65%. The non-cognitive variables and participation in the orientation course did not contribute additional information beyond the academic variables (French et al., 2005).

Few empirical studies, which use cognitive and non-cognitive factors to predict academic success in engineering, exist. The previous findings (Besterfield-Sacre et al., 1997; Brown, 1994; Burtner, 2003; Felder et al., 1993; French et al., 2005; House, 2000; LeBold & Ward, 1988; Shuman et al., 2003) revealed that non-cognitive factors could significantly contribute beyond cognitive factors. However, further research is needed to determine the joint relationship between cognitive and non-cognitive factors and how that relationship contributes to academic success in the pre-engineering curriculum.

Summary

High school background in quantitative content has a direct effect on the student's academic success in undergraduate coursework (Gainen, 1995). In addition to cognitive factors, students' attitudes relating to overall academic achievement can predict success in quantitative courses. These attitudes include expectation of success, their academic ability in relation to their peers, and confidence in their abilities (House, 1995c). By assessing these non-cognitive factors, college and university staff could predict academic success after the initial admission screening of applicants (Besterfield-Sacre et al., 1997). Limited research exists for the effects of cognitive and non-cognitive factors on long-term academic measures, such as cumulative college GPAs (House, 1995b; LeBold & Ward, 1988). Despite the fields of engineering having a quantitative content focus, fewer researchers have attempted to investigate the joint relationship between cognitive and non-cognitive factors and academic success in quantitative coursework.

The focus of this study was to determine if cognitive factors mediate the effect of non-cognitive factors on quantitative GPA and to determine if these cognitive and non-cognitive factors can predict admission status in engineering education. After reviewing the literature, the following cognitive and non-cognitive factors were selected for the statistical analysis based on the significant findings of empirical research studies.

Cognitive factors. Three cognitive factors were selected for incorporation in this study. The dominant predictor of academic success in engineering was standardized test scores, SAT and ACT, (Besterfield-Sacre et al., 1997; Blumner & Richards, 1997;

Brown, 1994; Buechler, 2004; Devens & Walker, 2001; French et al., 2005; Heinze et al., 2003; Harackiewicz et al., 2002; House, 1995a, 1995b, 2000; House et al., 1996; Lackey et al., 2003; LeBold & Ward, 1988; Moller-Wong & Eide, 1997; Shuman et al., 2003; Wesley, 1994; Zhang et al., 2004). High school rank was significant predictor of academic success in engineering (Besterfield-Sacre et al.; Buechler; Edge & Friedberg, 1984; French et al.; Harackiewicz et al.; House, 2000; Lackey et al.; LeBold & Ward; Moller-Wong & Eide, 1997; Shuman et al.; Smith & Schumacher, 2005; Wilhite et al., 1998; Zhang et al.). Lastly, to target quantitative ability specifically, high school math grades were found to be significant predictors of academic success in engineering (House et al.; LeBold & Ward; Sadler & Tai, 2001; Smith & Schumacher; Wilhite et al.).

Non-cognitive factors. Eight non-cognitive variables were chosen to be investigated based on the findings of the reviewed research: academic self-concept (Brown, 1994; Burtner, 2004, 2005; House, 1993, 1995a, 1995b, 1995c, 2000; Nixon & Frost, 1990), math self-concept (Burtner, 2004, 2005; House, 1995a, 1995b, 1995c; LeBold & Ward, 1988; Shuman et al., 2003), problem solving (Besterfield-Sacre et al., 1997; Brown; Burtner, 2004; Blumner & Richards, 1997; Lackey et al., 2003; LeBold & Ward; Litzinger et al., 2005; Shaughnessy et al., 1995), self-appraisal (Besterfield-Sacre et al.; Brown; Brown & Cross, 1993; Harackiewicz et al., 2002; House, 1993, 1995b), study habits (Besterfield-Sacre et al.; Blumner & Richards; Burtner, 2004; Harackiewicz et al.; Nixon & Frost; Wesley, 1994), need help (Besterfield-Sacre et al.), perceived difficulty (Besterfield-Sacre et al.), and academic difficulty (Besterfield-Sacre et al.).

CHAPTER III

METHODS

Numerous empirical studies have addressed the relationship between cognitive skills and academic success in undergraduate and engineering curriculums (Baron & Norman, 1992; Buechler, 2004; Burtner, 2004; Edge & Friedberg, 1984; House, 1995b; House et al., 1996; Smith & Schumacher, 2005; Wilhite et al., 1998). Limited research exists for predicting academic success using cognitive and non-cognitive factors (i.e., self-concept, study habits, and inquisitiveness) (House, 1995b, 2000). By increasing interest and mathematical skills, the percentage of college engineering graduates can increase (French et al., 2005; Wilhite et al.). Therefore, the purpose of this study was to determine if cognitive factors mediate the effect of non-cognitive factors on quantitative GPA and to determine if these cognitive and non-cognitive factors can predict admission status in engineering education. This study builds upon the findings of French et al., House (2000), and Shuman et al. (2003).

Participants

Participants in this study were from a sample of 3,052 undergraduate students who entered Auburn University in pre-engineering from the fall semester of 2000 through the fall semester of 2004. Table 1 displays the frequencies for each admission year. Of these cases, 2,276 participants were selected for the study because their survey responses could be matched with the standardized test scores and college grades provided by the

University Planning and Analysis Office. The fall semesters of 2000 through 2004 were selected because Auburn University switched from the quarter system to the semester system beginning with the fall term of 2000. This change to the academic calendar revised the pre-engineering curriculum when courses were consolidated for the 16-week semester system. The participants who entered engineering after fall 2004 have not had enough time to complete the pre-engineering curriculum.

Table 1

Frequencies by Academic Year

	Entire sample		Sample cases	
Year	*n*	%	*n*	%
2000	609	20.0	451	19.8
2001	608	19.9	454	19.9
2002	626	20.5	439	19.3
2003	641	21.0	494	21.7
2004	568	18.6	438	19.2
Total	3,052	100.0	2,276	100.0

Of the participants with a declared major in engineering, 1,857 (81.6%) were male, and 419 (18.4%) were female. The racial classification of the group was 1,885 (82.8%) White, 258 (11.3%) Black, and 133 (5.8%) students who reported they belonged to other racial groups. The majority of the participants (54.6%) reported a master's degree as the highest education level they expected to attain. The participants in this study represented 40 of the 50 U.S. states, and 1,644 (72.2%) reported Alabama as their home state. When asked to describe the place where they lived before enrolling in college, 736 (32.3%) participants reported small town, 654 (28.7%) reported suburbia, 534 (23.5%) reported large town, 176 (7.7%) reported big city, and 176 (7.7%) participants reported rural. The range of their high school graduating class size was less than 50 to more than 500 students with a median of 200.

Procedures

Eight on-campus orientation sessions were held during the summer prior to fall enrollment for each pre-engineering cohort in this study. During the first day of the orientation, the participants completed the College Freshman Survey. The administration of the survey took approximately 1 hour. If the participants were unable to attend the sessions, they were invited to attend a make-up session during the first week of fall semester.

Measures

College Freshman Survey. The College Freshman Survey (Halpin & Halpin, 1996) is a 248-item measure designed to assess variables related to success in engineering. The beginning questions elicited demographic information, standardized test scores, and high school grades. The remaining questions (200 items) determined the importance of various subjects, rank of abilities, likelihood of various events, and agreement with various statements. For the strength statements, the response scale progressed from a rating of 1, which represented *Very Weak*, to a rating of 5, which represented *Very Strong*. For the likelihood statements, the response scale progressed from a rating of 1, which represented *Very Unlikely*, to a rating of 4, which represented *Very Likely*. With the remaining non-cognitive items, respondents were asked to indicate the extent of their agreement using a 4-point scale, from a rating of 1, which represented *Strongly Disagree*, to a rating of 4, which represented *Strongly Agree*. These items were rationally combined to form 32 scales (Table 2) which measured possible influences for retention and attrition in engineering education. Based on the review of literature, 49 of the 248 items on the College Freshman Survey, which comprised eight non-cognitive factor scales, were selected for this study. Items 84, 190, 200, and 214 were reverse-coded before combining with other items to form the scales.

Table 2

Scales for the College Freshman Survey

	Scales	
Academic Difficulty	Like and Excel in English	
Academic Self-Concept	Likelihood of Leaving Auburn University	Self-Appraisal
Academic Success in Engineering	Likelihood of Leaving Engineering	Social Skills
Close Friendships	Locus of Control	Socioeconomic Status
Communication Skills	Math Self-Concept	Study Habits
Competitiveness	Need for Structure	Study Hard
Computer Capability	Need Help	Teacher Importance
Extrinsic Motivation	Note Taking	Team Membership
Intrinsic Motivation	Organizational Skills	Test Anxiety
Knowledge and Confidence	Perceived Difficulty	Work Ethnic
Leadership	Problem Solving	

In terms of non-cognitive factors, eight scales were created as follows:

1. *Math Self-Concept* consists of five items assessing one's preference for mathematics, self-assessed ability in mathematics, and grades in mathematics compared to other subjects.
2. *Self-Appraisal* consists of six items assessing one's strengths, weaknesses, and confidence in his or her ability to handle problems and change.
3. *Study Habits* consists of seven items assessing one's ability to stay focused on tasks, to recognize relevant information, to manage study time, and to self-assess study effectiveness.
4. *Problem Solving* consists of five items assessing one's ability to think analytically and critically, to recognize and solve problems, and to integrate knowledge and information.
5. *Academic Self-Concept* consists of four items assessing one's ability in mathematics, academic preparation for college, and motivation to achieve.
6. *Perceived Difficulty* consists of 11 items assessing one's loneliness during his or her freshman year of college, need for assistance from others, anxiety about the expectations of the curriculum, and inability to control time or events.
7. *Need Help* consists of six items assessing the likelihood of one needing assistance with test-taking, basic math, reading, writing, and study skills.
8. *Academic Difficulty* consists of five items assessing the likelihood of failing a course, performing less than expected in academics, becoming bored with the coursework, and becoming stressed with one's studies.

Reliability analyses were conducted to test that the scales provided internally consistent measurements. A Cronbach's alpha of .50 or greater was established as the criterion for reliability following Thorndike (1951). The established criterion for reliability had not changed since Kelly in 1929 also proposed .50 as the criterion. Hair, Black, Babin, Anderson, and Tatham (2006) suggested .60 as a criterion for reliability. The reliability coefficients for the eight non-cognitive factor scales were good (ranging from .63 to .89 with a median of .71). (See Table 3.) The results suggest that the scales within the survey are internally consistent measures.

Table 3

Alpha Reliability Coefficients for Non-Cognitive Factor Scales

Scale	Coefficient Alpha
Math Self-Concept	.89
Self-Appraisal	.66
Study Habits	.72
Problem Solving	.79
Academic Self-Concept	.69
Perceived Difficulty	.70
Need Help	.63
Academic Difficulty	.63

Institutional data. Data were obtained through the University Planning and Analysis Office for freshmen who entered the College of Engineering from 2000 through 2004. The collected data included (a) ACT composite, English, math, reading and science scores; (b) SAT quantitative and verbal scores; (c) grades in pre-engineering quantitative courses; and (d) pre-engineering GPAs.

The ACT is a curriculum-based assessment that is composed of four subtests: English, Mathematics, Reading, and Science. The purpose of this assessment is to measure the knowledge and skills gained during high school and the expectations for success in post-secondary institutions. The score on each subtest ranges from 1 to 36. These subtest scores are averaged to create the ACT composite score, which ranges from 1 to 36. The estimated reliability coefficient for the ACT composite score is .96 (Noble et al., 2006). For the purposes of this study, the score from the ACT Math Subtest was used.

The SAT is composed of a verbal and quantitative subtest. The purpose of this assessment is similar to the ACT. The score for each subtest ranges from 200 to 800. The scores from the two subtests are added together to create the total SAT score. The estimated reliability for the SAT quantitative subtest is .92 (Ewing, Huff, Andrews, & King, 2005). For purposes of this study, the quantitative score was used for those participants who only took the SAT.

Design and Analysis

Exploratory factor analysis. The sample was randomly divided into two databases of comparable size. With one database, an exploratory factor analysis using principal axis factoring with an oblimin rotation was conducted using the following scales from the College Freshman Survey: Math Self-Concept, Self-Appraisal, Perceived Difficulty, Problem Solving, Need Help, Academic Difficulty, Study Habits, and Academic Self-Concept. The purpose of this factor analysis was to discover the factor structure of the selected items and the correlations between the factors. This method consisted of a principal component analysis followed by rotation of factors that had eignvalues greater than 1.00. A criterion of .40 or higher was established for the structure coefficients (Meyers et al., 2006).

The Kaiser-Meyer-Olkin (KMO) Measure of Sampling is a summary index, which ranges from 0 to 1, of the interrelatedness among the items and the extent to which the items will yield an appropriate factor analysis. With the randomly selected sample, the KMO was .91, which exceeds the suggested minimum value of .70. Bartlett's Test of Sphericity (approximate $\chi^2 = 22{,}413.24$, $p < .001$) indicates that the intercorrelations among the items are statistically significant and of a sufficient magnitude to conduct a factor analysis (Meyers et al., 2006).

With a total of 49 items, 11 factors emerged with initial eigenvalues above 1.0. The communalities ranged from .34 to .76. After an oblimin rotation was conducted, four factors were eliminated because they had one to two items meaningfully related to the factor. With this analysis and modifications, which contained 36 items, 47.57% of the variance was explained.

Seven non-cognitive factors were created as a result of the exploratory factor analysis. Due to the confidentiality of the secure test items, the specific items with their respective factor loadings could not be presented. Factor 1, Lack of Confidence in Academic Abilities, contains four items with the following factor loadings: -.51, -.64, -.68, and -.71. Factor 2, Mathematical Ability, contains seven items with the following factor loadings: .62, .79, .79, .80, .84, .86, and .86. Factor 3, Self-Appraised Abilities, contains four items with the following factor loadings: .55, .57, .67, and .75. Factor 4, Adaptability, contains five items with the following factor loadings: -.43, -.45, -.66, -.68, and -.73. Factor 5, Difficulty with Problem Solving, contains five items with the following factor loadings: -.70, -.71, -.73, -.74, and -.78. Factor 6, Academic Frustration, contains four items with the following factor loadings: .44, .65, .67, and .71. Factor 7, Distractibility, contains seven items with the following factor loadings: .48, .49, .52, .54, .67, .76, and .77.

The reliability coefficients were conducted for the seven revised non-cognitive factor scales. The results indicated that the coefficients were good (ranging from .59 to .90 with a median of .70). (See Table 4.)

Table 4

Alpha Reliability Coefficients for Revised Non-Cognitive Factor Scales

Scale	Coefficient Alpha
Lack of Confidence in Academic Abilities (LCAA)	.70
Mathematical Ability (MA)	.90
Self-Appraised Abilities (SAA)	.59
Adaptability (A)	.62
Difficulty with Problem Solving (DPS)	.79
Academic Frustration (AF)	.61
Distractibility (D)	.74

Confirmatory factor analysis. With the second database, a confirmatory factor analysis was conducted using AMOS 7.0 to determine how the theoretical structure fits with the data and to crossvalidate the factor structures created with the exploratory factor analysis.

According to Meyers et al. (2006), acceptable model fit indexes include the Comparative Fit Index (CFI) and the Root Mean Square Error of Approximation (RMSEA). A value of .95 or greater for the CFI is deemed as an acceptable fit. For the RMSEA, a value of .08 or less indicates good fit. The model had a significant chi-square

(χ^2 = 6,964.196; p = .00) and a low CFI (.839) but low RMSEA (.05). Since the sample contained missing data, modification indices could not be utilized. Based on the RMSEA, the model was deemed to have good fit with the data. Table 5 displays the standardized beta weights for each item.

Table 5

Standardized Beta Weights by Confirmatory Factor Analysis for the Seven-Factor Model

	Factor		
Item	LCAA	MA	SAA
128	.753		
126	.611		
127	.601		
135	.493		
149		.868	
177		.806	
124		.849	
190		.751	
137		.742	
208		.758	
84		.593	
154			.584
169			.549
213			.487
142			.458

(Table 5 continues)

(Table 5 continued)

	Factor			
Item	A	DPS	AF	D
243	.562			
173	.542			
219	.529			
206	.499			
200	.442			
111		.715		
112		.712		
132		.691		
116		.689		
131		.527		
101			.638	
100			.629	
88			.498	
93			.322	
201				.759
155				.707
214				.576
170				.515
168				.500
160				.407
143				.394

Structural equation model. Structural equation modeling is an extension of the general linear model and the multiple regression analysis procedure. An advantage of structural equation modeling is that it can be used to analyze the relationships between latent variables and the relationship between the latent variables and multiple measures.

Unobserved latent variables cannot be measured directly so they are indicated by observed variables. Also, it is applicable to and appropriate for longitudinal data since those datasheets generally consist of a large sample size. The goal of structural equation modeling is to determine if the hypothesized theoretical model, which depicts the causal pattern of relationships that was determined a priori, is reflected by the empirical data (Lei & Wu, 2007).

The estimation procedure for this analysis was maximum likelihood. Maximum likelihood is similar to the generalized least squares method because they both give proportional weight to the variables based on the interrelationships. As an alternative to least squares, which compares error or deviations from the mean score, maximum likelihood estimates assume the data are normally distributed with some unknown mean and variance. These unknown values are estimated at the highest likelihood of the actual data and often are required iterative or repetitious solutions. Thus, the procedure maximizes the probability of sampling the population (Meyers et al., 2006).

Items within each factor were combined to simplify the model (Meyers et al., 2006). After the initial frequencies, descriptives, and bivariate correlation were assessed, a structural equation model was created using AMOS 7.0 to determine the relationship between the cognitive and non-cognitive factors and quantitative GPA in the pre-engineering curriculum with 60% of the sample. The non-cognitive factors were exogenous variables for the cognitive factors. The cognitive factors were exogenous variables for the dependent and endogenous variable, quantitative GPA during the pre-engineering curriculum. A cross-validation sample, which contained the remaining 40%

of the sample cases, was used to confirm the findings of the first structural model analysis.

Seven revised factor scales served as multiple measures of the latent construct of non-cognitive skills. These factor scales were employed as indictors of a single construct after a series of exploratory and confirmatory factor analyses. To simplify the model, the non-cognitive scales were grouped into two factors based on their intercorrelations. Factor 1 contained Lack of Confidence in Academic Abilities; Mathematical Ability; Self-Appraised Abilities; and Difficulty with Problem Solving. Factor 2 contained Adaptability, Academic Frustrations, and Distractibility.

The cognitive factors included three measures: ACT math scores, high school math grades, and high school ranks.

For 292 cases, the participants only took the SAT. A bivariate correlation was conducted with the SAT quantitative and ACT math scores to determine the extent of their relationship given this sample. The results yielded by the SAT quantitative and ACT math scores were highly correlated ($r = .79$; $p < .001$). To linear equate the SAT quantitative and ACT math scores, a multiple regression analysis was conducted (Peterson, Kolen, & Hoover, 1989). Of the participants who took both the ACT and SAT, a bivariate correlation was conducted to determine the validity of the analysis between the adjusted ACT math and the actual ACT math scores ($r = .79$; $p < .001$). The adjusted ACT math scores were used for the participants who only took the SAT.

On the College Freshman Survey, self-reported grades were collected using the following response scale: 1 = A+, 2 = A, 3 = A- to B+, 4 = B to B-, 5 = C+ to C-, 6 = D+ or less, and 7 = did not take the course. The raw data was recoded to reflect the following scale: 1 = D+ or less, 2 = C+ to C, 3 = did not take the course, 4 = B to B-, 5 = A- to B+, 6 = A, and 7 = A+. The 7-point scale was used to weight empirically the responses in order to account for the class not being taken in high school and to differentiate between A+, A, and A-. Mean high school math grade was computed using the criterion of self-reported responses in at least three courses. Descriptives for the grades in the high school mathematics courses (i.e., algebra I, algebra II, geometry, trigonometry, and calculus) (Shettle et al., 2007) were assessed. The high school math grades for the participants ranged between an A and B+. Of these participants, 35% did not take a calculus course in high school. Table 6 displays the means and standard deviations for each high school mathematics course.

Table 6

Means and Standard Deviations for Each High School Mathematics Course

Scale	*M*	*SD*
Algebra I	5.63	1.39
Geometry	5.57	1.36
Algebra II	5.48	1.39
Trigonometry	5.00	1.60
Calculus	4.46	1.65

According to Edge and Friedberg (1984), high school GPA and high school rank are highly correlated because they are similar measures of long-term achievement. In this study, high school rank will be used in place of high school GPA. High school ranks were collected from the self-reported measure, the College Freshman Survey. The participants responded using the following scale: 1 = lowest 40%, 2 = middle 20%, 3 = next 10%, 4 = next 10%, 5 = next 10%, 6 = next 7%, and 7 = highest 3%. Kuncel, Credé, and Thomas

(2005) found with their meta-analysis that self-reported grades had construct validity as a measure of achievement. Furthermore, self-reported grades and class ranks tend to be reliable measures of the actual grades and high school ranks when reported by college students with reasonably high cognitive abilities. The reliabilities are likely to increase by asking specific grades in specific classes.

To measure discriminate validity, a bivariate correlation was conducted using the three cognitive and seven revised non-cognitive factors. With a Pearson correlation coefficient less than or equal to .80 as a criterion (Meyers et al. 2006), these results suggested that the factors have discriminate validity and are not measuring the same concept. Table 7 displays the intercorrelation matrix for the cognitive and non-cognitive factors. The means and standard deviations for the cognitive and revised non-cognitive factors are presented in Table 8.

The dependent variable of quantitative GPA in the pre-engineering curriculum was measured with at least two quantitative courses in the pre-engineering curriculum at Auburn University. A quantitative course was defined as a college course whose conceptual foundation is based in mathematics (Gainen & Willemsen, 1995). Table 9 displays the courses from the pre-engineering curriculum, which were considered quantitative courses in this study. The final letter grade in each quantitative course was coded using the 4-point scale (i.e., A = 4, B = 3, C = 2, D = 1, and F = 0) and was averaged together to create the quantitative GPA. The mean score was 2.33 with a standard deviation of 1.03. A bivariate correlation was conducted to determine the relationship between the pre-engineering quantitative GPA and the total pre-engineering GPA. A strong positive relationship existed between the GPAs ($r = .87$; $p < .001$).

Table 7

Intercorrelations for the Cognitive and Revised Non-Cognitive Factors

Scale	1	2	3	4	5	6	7	8	9	10
1. Lack of Confidence in Academic Abilities	--	.37**	.41**	.25**	.47**	.32**	.42**	.19**	.29**	.30**
2. Mathematical Ability		--	.13**	.16**	.33**	.25**	.16**	.44**	.54**	.26**
3. Self-Appraised Abilities			--	.27**	.35**	.20**	.28**	-.03	.03	.02
4. Adaptability				--	.29**	.38**	.32**	-.05*	.07**	-.02
5. Difficulty with Problem Solving					--	.28**	.18**	.26**	.14**	.13**
6. Academic Frustration						--	.41**	.08**	-.06*	-.02
7. Distractibility							--	.06**	.14**	.19**
8. ACT Math Scores								--	.43**	.34**
9. High School Math Grades									--	.58**
10. High School Ranks										--

Note: * $p < .05$; ** $p < .01$.

Table 8

Means and Standard Deviations for the Cognitive and Revised Non-Cognitive Factors

Scale	*M*	*SD*
Lack of Confidence in Academic Abilities	3.79	0.49
Mathematical Ability	3.37	0.56
Self-Appraised Abilities	3.13	0.34
Adaptability	2.30	0.41
Difficulty with Problem Solving	3.88	0.55
Academic Frustration	2.29	0.46
Distractibility	2.46	0.43
ACT Math Scores	26.58	4.23
High School Math Grades	5.23	1.07
High School Ranks	4.90	1.70

Table 9

List of Possible Quantitative Courses in Pre-Engineering Curriculum

Course	Number
College Algebra	MA1000
Pre-Calculus Trigonometry	MA1130
Pre-Calculus Algebra Trigonometry	MA1150
Calculus I	MA1610
Honors Calculus I	MA1617
Calculus II	MA1620
Honors Calculus II	MA1627
Calculus for Engineering and Science I	MA1710
Calculus for Engineering and Science II	MA1720
Calculus III	MA2630
Calculus for Engineering and Science III	MA2730
Survey of Chemistry I	CH1010
Survey of Chemistry II	CH1020
Fundamentals of Chemistry I	CH1030
Fundamentals of Chemistry II	CH1040
General Chemistry I	CH1110
Honors General Chemistry I	CH1117
General Chemistry II	CH1120
Honors General Chemistry II	CH1127
Foundations of Physics	PH1000
General Physics I	PH1500
General Physics II	PH1510
Engineering Physics I	PH1600
Honors Physics I	PH1607
Engineering Physics II	PH1610
Honors Physics II	PH1617

Discriminant function analysis. A discriminant function analysis was conducted using the 60% sample to develop a weighted linear combination to predict group membership (i.e., admitted to engineering, switched to another major at the university, or left the university unsuccessful). The analysis used admission status as the grouping variable and the cognitive and revised non-cognitive factors as the independent variables. To be admitted to the Samuel Ginn College of Engineering, the participants were required to have at least a 2.2 GPA. Participants who were identified as switched majors had at least a 2.2 GPA but chose to pursue another major outside the field of engineering at Auburn University. For those participants who left the university unsuccessful, they earned a GPA below 2.2 and left the university without earning a degree for unknown reasons. For the admission year 2003, 11 participants were still enrolled as pre-engineering majors, and 39 participants from the 2004 admission year were still enrolled as pre-engineering majors. They were excluded from the sample for the purposes of this analysis. Table 10 provides the frequencies for admission status by admission year.

Table 10

Frequencies for Admission Status by Academic Year

	Admitted to engineering		Switched majors		Left unsuccessful		Total	
Year	*n*	%	*n*	%	*n*	%	*n*	%
2000	262	58.1	89	19.7	100	22.2	451	100.0
2001	264	58.1	83	18.3	107	23.6	454	100.0
2002	279	63.5	85	19.4	75	17.1	439	100.0
2003	267	55.3	100	20.7	116	24.0	483	100.0
2004	252	63.2	78	19.5	69	17.3	399	100.0
Total	1,324	59.5	460	20.7	442	19.8	2,226	100.0

Summary

Participants in this study were a sample of undergraduate students who entered the pre-engineering curriculum in the fall semester of 2000 through the fall semester of 2004. These participants completed the College Freshman Survey (Halpin & Halpin, 1996). In addition, institutional data were collected for the participants' standardized test scores and pre-engineering course grades. An exploratory and confirmatory factor analyses were conducted to create and validate seven revised non-cognitive factors. A structural equation model analysis and discriminant factor analysis were conducted to answer the two research questions. In these statistical procedures, the seven revised non-cognitive factors, three cognitive factors, and dependent variable, quantitative GPA, were analyzed. The results are presented in Chapter IV.

CHAPTER IV

RESULTS

The research was guided by two research questions: (a) Do cognitive factors mediate the effect of non-cognitive factors on quantitative GPA? and (b) Can cognitive and non-cognitive factors predict engineering admission status?

Relationship between Cognitive and Non-Cognitive Factors and Quantitative GPA

A structural equation model was created using AMOS 7.0 to determine the relationship between cognitive and non-cognitive factors and quantitative GPA in the pre-engineering curriculum with 60% of the sample (n = 1,375). Directional arrows were used to indicate the hypothesized causal or direct relationship. The curved arrows were used to indicate unexplained covariance or correlations. The rectangular boxes indicated the observed variables, and the elliptical shapes indicated the latent, or unobserved, variables (Meyers et al., 2006).

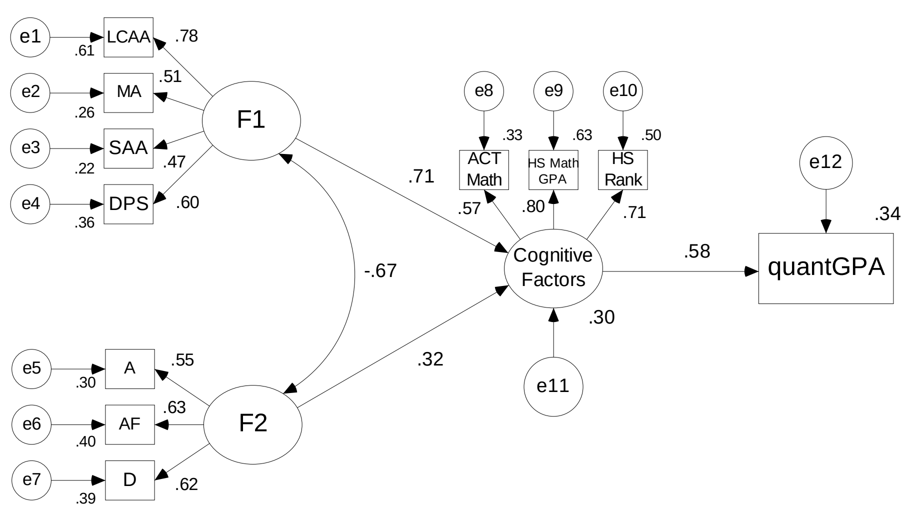
The initial model was recursive, which means the paths were directional between the predictor variables and the outcome variable (Hair et al., 2006). The resulting model containing two latent variables measured by seven non-cognitive factor measures and one latent variable measured by three cognitive factor measures is presented in Figure 1.

With the criteria for acceptable model fit indexes, according to Meyers et al. (2006), a value of .95 or greater for the GFI and CFI is deemed as an acceptable fit. For the RMSEA, a value of .08 or less indicates good fit. This initial model had a low GFI

(.896) and CFI (.786), high RMSEA (.123), and a significant chi-square ($\chi^2 = 898.894$; $p < .001$). Thus, the model needs to be modified to reflect the empirical data. This initial model had a R^2 of .30 for the cognitive factors, which means the two latent variables measured by the seven non-cognitive factors accounted for 30% of the variance in the latent variable, cognitive factors. The R^2 for quantitative GPA, a single-item measure, was .34. These results suggested that the non-cognitive and cognitive factors explained 34% of the variance in the dependent variable, quantitative GPA.

Figure 1

Structural Equation Model



The initial hypothesized model was rejected based on the goodness-of-fitness statistics. With the modification indices, a restricted model, presented in Figure 2, was created. The model had a higher GFI (.977) and CFI (.961). The RMSEA value was .081, which improved by .042. The chi-square was significant ($\chi^2 = 131.110$; $p < .001$); however, the chi-square tends to be overly sensitive with large sample sizes (Meyers et al., 2006). All of these indices indicated a good fit between the restricted model and the empirical data.

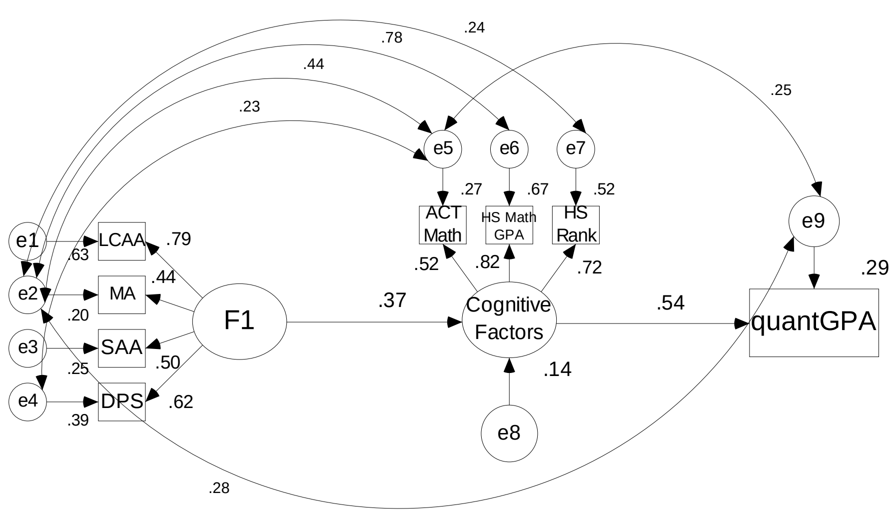
The restricted model had a R^2 of .14 for the cognitive factors and a R^2 of .29 for the quantitative GPA. The R^2_{change} between the initial model and the restricted model for cognitive factors was .16. The F_{change} formula was used to determine if the change in R^2 was statistically significant (Pedhazur, 1997):

$$F_{\text{change}} = \frac{[(R^2_{\text{initial}} - R^2_{\text{restricted}}) / (k_{\text{initial}} - k_{\text{restricted}})]}{[(1 - R^2_{\text{initial}}) / (n - k_{\text{initial}} - 1)]},$$

where $R^2_{\text{initial}} = R^2$ for the initial model, $R^2_{\text{restricted}} = R^2$ for the restricted model, k_{initial} = number of predictors for the initial model, $k_{\text{restricted}}$ = number of predictors for the restricted model, and n = number of participants in the sample.

Figure 2

Structural Equation Model: Restricted Model



The change in R^2 was statistically significant for the latent variable, cognitive factors, [$F(3, 1367) = 937.37$; $p < .001$]. The overall variance accounted for in quantitative GPA using the latent variable measured by the four non-cognitive and the latent variable measured by the three cognitive factors reduced by 5%, .34 with the initial model and .29 with the restricted model. The change in R^2 was statistically significant [$F(3, 1364) = 310.00$; $p < .001$]; therefore, by restricting the model, the amount of variance in quantitative GPA which was explained was significantly affected. The residuals were correlated according to the model specifications and modification indices. These correlations ranged from .23, weak to moderate relationship, to .78, strong relationship. Subsequently, the variance explained in the outcome variables, cognitive factors and quantitative GPA, reduced by correlating these residuals.

The standardized beta weights for the restricted model ranged from .44 to .82 and were statistically significant at or below the .05 level. A criterion of .40 or higher was established for the standardized beta weights as a measure of association (Meyers et al., 2006). These results suggested the observed variables were statistically significant measures for the latent variables, and these beta weights indicated the model has construct validity. The standardized beta weight (.37) for the path from the non-cognitive factors to the cognitive factors was statistically significant and considered to have a moderate relationship. Likewise, the standardized beta weight (.54) for the path from the cognitive factors to the outcome variable, quantitative GPA, was also statistically significant and considered as a strong relationship.

According to Hair et al. (2006), a direct effect is defined as the relationship between two constructs. An indirect effect is defined as the relationship that results from the sequence of two or more direct effects. Non-cognitive variables did not have a direct effect on the quantitative GPA, but they did have an indirect effect through the cognitive variables. The results suggested that cognitive factors mediate the effects of lack of confidence in academic abilities, mathematical ability, self-appraised abilities, and difficulty with problem solving on the quantitative GPA. The interpretation for these effects followed the criterion established for correlation coefficients where .10 is weak, .30 is moderate, and .50 is strong according to Cohen (Meyers et al., 2006). The direct effect for the relationship between cognitive factors and quantitative GPA was strong (.54), and the direct effect for the relationship between non-cognitive and cognitive factors was moderate (.37). The indirect effects between non-cognitive factors and quantitative GPA were weak to moderate (.20). These effects were interpreted as a measure of association between the predictor and outcome variables. Due to the simplified nature of this model, these effects paralleled the standardized beta weights.

As a method of validating the initial structural equation model analysis, a 40% cross-validation model (n = 901) was analyzed using the two latent variables, non-cognitive factors 1 and 2, and one latent variable defined as cognitive factors. The results are presented in Figure 3. With the same criteria for acceptable model fit indexes according to Meyers et al. (2006), the initial cross-validation model had a low GFI (.876) and CFI (.776), high RMSEA (.132), and a significant chi-square ($\chi^2 = 684.698$; $p < .001$).

The cross-validation sample was analyzed using the same restricted model from the 60% sample. Results are presented in Figure 4. The cross-validation restricted model had a higher GFI (.974) and CFI (.958). The RMSEA value was .086, which improved by .046. The chi-square was significant ($\chi^2 = 98.765$; $p < .001$). All of these indices indicated a good fit between the cross-validation restricted model and data.

Figure 3

Cross-validation Structural Equation Model

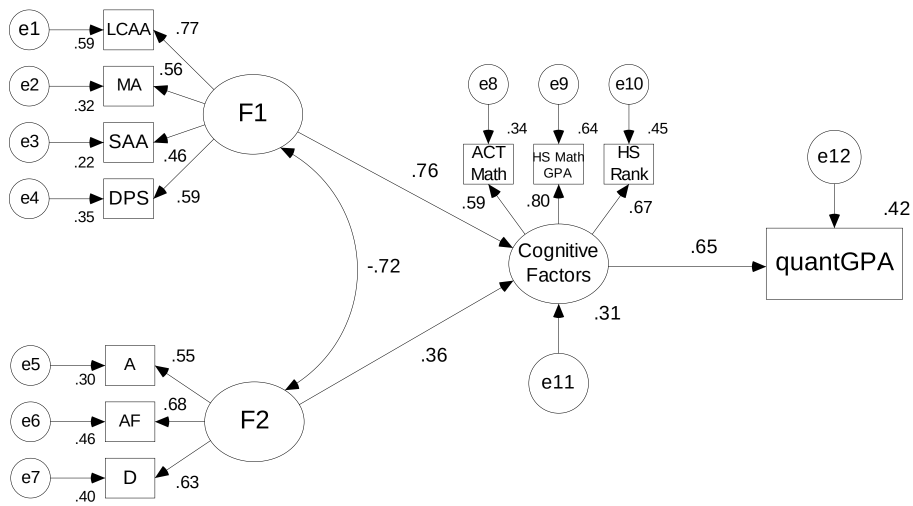
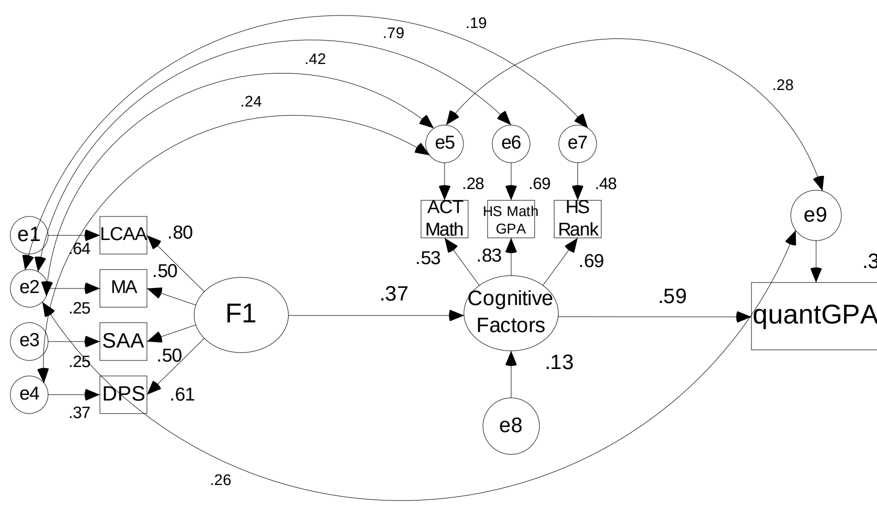


Figure 4

Cross-validation Structural Equation Model: Restricted Model



The test of significance for the change in R^2 (Pedhazur, 1997) was used to compare the change in R^2 from the full model to the restricted model. The full model had a R^2 of .31 for the cognitive factors, and the restricted model had a R^2 of .13 for the cognitive factors. The R^2_{change} between the full model and the restricted model for cognitive factors was .18. [$F(3, 893) = 77.65$; $p < .001$]. The full model had a R^2 of .42 for the quantitative GPA, and the restricted model had a R^2 of .35 for the quantitative GPA. The overall variance accounted for in quantitative GPA using the latent variable measured by the four non-cognitive and the latent variable measured by the three cognitive factors reduced by 7%. The change in R^2 was statistically significant [$F(3, 890) = 35.80$; $p < .001$].; therefore, by restricting the model, the amount of variance in quantitative GPA which was explained was significantly affected.

The standardized beta weights for the restricted model ranged from .50 to .83 and were statistically significant at or below the .05 level. A criterion of .40 or higher was established for the standardized beta weights as a measure of association (Meyers et al., 2006). These results suggested that the observed variables were significant measures for the latent variables. The standardized beta weight (.37) for the path from the non-cognitive factors to the cognitive factors was statistically significant. Likewise, the standardized beta weight (.59) for the path from the cognitive factors to the outcome variable, quantitative GPA, was also statistically significant. These statistically significant beta weights indicated that the model has construct validity. The results suggested that cognitive factors mediate the effects of lack of confidence in academic abilities, mathematical ability, self-appraised abilities, and difficulty with problem solving on the quantitative GPA. As a mediator variable, cognitive factors serve as a construct that intervenes between the two other constructs, non-cognitive variables and quantitative GPA.

The direct effect for the relationship between cognitive factors and quantitative GPA was strong (.59), and the direct effect for the relationship between non-cognitive and cognitive factors was moderate (.37). The indirect effects between non-cognitive factors and quantitative GPA were weak to moderate (.22). Again, these results suggested that cognitive factors mediate the effects of lack of confidence in academic abilities, mathematical ability, self-appraised abilities, and difficulty with problem solving on the quantitative GPA. The cross-validation analysis confirmed the results yielded with the initial analysis.

Effects of Cognitive and Non-Cognitive Factors on Engineering Admission Status

A discriminant function analysis was conducted to develop a weighted linear combination to predict group membership (i.e., admitted to engineering, switched to another major at the university, or left the university unsuccessful). Admission status was the grouping variable. The sample for this analysis was the same sample used for the initial structural equation modeling analysis. This randomly selected sample included 60% of the participants (n = 1,347). Betz (1987) recommended a cross-validation procedure when using discriminant function analysis for predictive purposes. Because the nature of the analysis is to maximize the linear relationship, there is a tendency to overestimate the accuracy of the classification.

The cognitive and non-cognitive factors included in the restricted structural equation model (lack of confidence in academic abilities, mathematical ability, self-appraised abilities, and difficulty with problem solving, adjusted ACT math scores, high school math grades, and high school ranks) were used as the independent variables. This analysis was appropriate to understand the differences between two or more groups and to determine the predictor variables that characterize the group differences. Similar to the multiple regression analysis procedure, a discriminant function analysis yields a linear equation with beta weights to maximize the predictability of the group membership (Betz, 1987).

Results of the discriminant function analysis characterizing each admission status with the non-cognitive and cognitive factors with are presented in Table 11. The analysis revealed adjusted ACT math scores, high school math grades, high school ranks, lack of confidence in academic ability, and difficulty with problem solving formed Function 1, and mathematical ability and self-appraised abilities formed Function 2. Canonical correlation is equivalent to an eta computed through an analysis of variance procedure and interpreted using the guidelines for correlation coefficients (Betz, 1987). For Function 1, the canonical correlation, a measure of association between the discriminant scores and group membership, was .38, $p < .001$, meaning the function has a moderate effect size. For Function 2, the canonical correlation was .09. Function 2 was not statistically significant, $p = .13$. Thus, it will not be used for subsequent analysis or discussion.

Table 11

Correlation of Predictor Variables with Discriminant Functions (Structure Matrix) and Standardized Discriminant Functions Coefficients

	Correlation		Standardized	
Predictor variable	Function 1	Function 2	Function 1	Function 2
Adjusted ACT math score	.79*	.07	.58	-.24
High school math grades	.76*	.06	.41	-.44
High school rank	.64*	-.08	.18	-.02
Lack of confidence in academic ability	.47*	.18	.34	-.09
Mathematical ability	.48	.86*	-.09	1.21
Difficulty with problem solving	.27*	.21	-.03	-.03
Self-appraised abilities	-.02	.21*	-.14	.10

* = largest absolute correlation between variable and discriminant function.

An eigenvalue is the ratio of between-groups to within-groups sum of square and is on a continuum from 0 to1 (Betz, 1987; Hair et al., 2006). If the eigenvalue is closer to 1, the function is considered good. The eigenvalue for Function 1 was .17, which means 17% of the variance was accounted for using Function 1.

The group centriod, the mean of the discriminant scores within a group, is calculated by applying the discriminant beta weights to the group means on each variable (Betz, 1987). With Function 1, participants who were admitted to the College of Engineering were likely to have higher cognitive factors, less difficulty with problem solving, and more confidence in their academic abilities ($z = 0.30$); however, participants who were unsuccessful (GPA < 2.2) were likely to have lower cognitive factors, more difficulty with problem solving, and less confidence in their academic abilities ($z = -0.74$). The centriod for the participants who switched majors at the university was

-0.16, which means the function did not discriminate with these characteristics.

A formula for the optimally weighted combination of predictor variables, predicted discriminant score (D), was created using the discriminant functions (Betz, 1987):

$$D = .145(\text{ACT}) + .409(\text{MATH}) + .111(\text{RANK}) + .717(\text{LCAA}) \\ + -.060(\text{DPS}) + -.167(\text{MA}) + -.413(\text{SAA}) + -7.170,$$

where ACT = adjusted ACT math scores, MATH = high school math grades, RANK = high school ranks, LCAA = lack of confidence in academic ability, DPS = difficulty with problem solving, MA = mathematical ability, and SAA = self-appraised abilities. After computing this variable, the predicted discriminant scores were converted into z scores to standardize them. The cross-validation cases were selected ($n = 879$) to apply the linear function developed with the initial discriminant function analysis. An analysis of variance (ANOVA) was conducted with the cross-validation sample to determine group difference between the participants who were admitted to engineering, switched to another major at the university, and left the university unsuccessfully using the synthetic dependent variable, the standardized predicted discriminant score.

The assumption of equal variance was not violated according to Levene's Test of Equality of Error Variances [$F(2, 876) = 0.06$; $p = .94$]. The results revealed a statistically significant difference among the three groups [$F(2, 876) = 76.65$; $p < .001$; $\eta^2 = .15$]. Table 12 displays the means and standard deviations by group. As a follow-up procedure, a Bonferroni post hoc analysis was conducted, which revealed statistically significant differences for all three pairwise comparisons. The greatest mean difference was between the participants who were admitted to engineering and those participants who left the university academically unsuccessful. Table 13 presents the pairwise comparisons by group.

Table 12

Means and Standard Deviations by Group

Scale	*M*	*SD*
Admitted to Engineering	0.45	0.91
Switched Majors	-0.09	0.89
Left Unsuccessful	-0.46	0.89

Table 13

Post Hoc Test Results: Mean Differences by Group

	Mean difference		
Scale	Admitted to engineering	Switched majors	Left unsuccessful
Admitted to Engineering	--		
Switched Majors	0.54*	--	
Left Unsuccessful	0.90*	0.37*	--

*Mean difference was statistically significant at the .05 probability level.

The statistical significance of the difference between the canonical correlation and the eta square from the ANOVA conducted with the cross-validation sample was determined using Fisher's z_r transformation to convert the correlation coefficients into *z* scores. With the transformed correlations, the difference in the two *z* scores was divided by the standard error of the difference (Ferguson & Takane, 1989). The algorithm was utilized to determine if the discriminant function, which was created with the analyzed sample, was generalizable to the holdout sample:

$$z = \frac{z_{r1} - z_{r2}}{\sqrt{[1/(n_1 - 3) + 1/(n_2 - 3)]}},$$

where z = difference in z scores, z_{r1} = Fisher's z_r transformation for the analyzed sample, z_{r2} = Fisher's z_r transformation for the cross-validation sample, n_1 = number of participants for the analyzed sample, and n_2 = number of participants for the cross-validation sample. The canonical correlation for the analyzed sample was .38. The square root of the eta square (.15) from the ANOVA with the cross-validation sample was .39. The Fisher's z_r transformation for the analyzed sample was .40, and the Fisher's z_r transformation for the cross-validation sample was .41. With the formula, the difference in z scores was 0.00, which indicated that there was not a statistically significant difference between the analyzed and cross-validation samples. Thus, the formula created with the analyzed sample was generalizable to the holdout sample.

The overall percentage of correctly classified cases was 51.6% (see Table 14). The participants who left the university unsuccessful were more accurately classified (60.8%). For the participants who were admitted to the College of Engineering, 56.1% of them were classified correctly. These results suggested that stronger cognitive and non-cognitive skills could yield higher quantitative GPAs. More specifically, academic preparation, problem solving, and perception of overall academic abilities could subsequently increase the quantitative GPAs.

With higher GPAs, it is likely that those participants who are interested in engineering would have an increased probability of admission to the College of Engineering. Approximately one third of the participants who switched majors were classified in each of the categories. The results suggested that cognitive and non-cognitive factors do not discriminate for the participants who are academically successful but choose other majors at the university. Thus, they likely differ with their interest level for the field of engineering.

Table 14

Classification Analysis for Admission Status

		Admitted to engineering		Switched majors		Left unsuccessful	
Actual group membership	*n*	*n*	%	*n*	%	*n*	%
Admitted to Engineering	809	454	56.1	158	19.5	197	24.4
Switched Majors	270	99	36.7	78	28.9	93	34.4
Left Unsuccessful	268	56	20.9	49	18.3	163	60.8

Note: Overall percentage of correctly classified cases = 51.6%.

With the analyzed sample, a cross-validation procedure was conducted during the discriminant function analysis for obtaining a cross-validated classification table (Table 15). The overall percentage of correctly classified cases (50.6%) was nearly equivalent to the initial analysis. Similar results were seen with the rate of correctly classified participants in the admitted to engineering group (56.0%) and those participants who left unsuccessfully (59.7%). In addition, the participants who switched majors were classified across the three groups without differentiation.

Table 15

Cross-validation: Classification Analysis for Admission Status

Actual group membership	*n*	Admitted to engineering *n*	%	Switched majors *n*	%	Left unsuccessful *n*	%
Admitted to Engineering	809	453	56.0	159	19.7	197	24.4
Switched Majors	270	105	38.9	69	25.6	96	35.6
Left Unsuccessful	268	56	20.9	52	19.4	160	59.7

Note: Overall percentage of correctly classified cases = 50.6%.

Means and standard deviations were conducted for the quantitative GPA, three measures for the latent variable (cognitive factors), and the four measures for the latent variable (non-cognitive factors) to compare the three groups according to the results of the discriminant function analysis. The means and standard deviations by group for the initial analysis sample are presented in Table 16. The quantitative GPA, adjusted ACT math scores, high school math grades, high school ranks, and mathematical ability were higher for the participants who were admitted to engineering. The participants who left the university unsuccessfully reported higher levels of agreement with lack of confidence in academic ability and difficulty with problem solving. Due to the inverse nature of the lack of confidence in academic ability and difficulty with problem solving, the lower numerical values represent higher levels of agreement. The means and standard deviations were similar across the three groups for self-appraised abilities, which were confirmed by the low standardized beta weight with the discriminant function analysis. Similar descriptives are displayed in Table 17 for the cross-validation sample.

Table 16

Means and Standard Deviations by Group

	Admitted to engineering		Switched majors		Left unsuccessful	
Scale	*M*	*SD*	*M*	*SD*	*M*	*SD*
Quantitative GPA	2.78	0.81	2.13	0.95	1.37	0.83
Adjusted ACT Math Scores	27.54	4.08	26.01	3.92	24.23	3.86
High School Math Grades	5.47	0.99	5.10	1.02	4.68	1.01
High School Ranks	5.22	1.57	4.76	1.69	4.12	1.75
Lack of Confidence in Academic Ability	3.86	0.47	3.73	0.50	3.62	0.50
Difficulty with Problem Solving	3.91	0.52	3.82	0.56	3.76	0.54
Mathematical Ability	3.47	0.51	3.26	0.54	3.22	0.59
Self-Appraised Abilities	3.12	0.33	3.11	0.37	3.13	0.34

Table 17

Cross-Validation: Means and Standard Deviations by Group

	Admitted to engineering		Switched majors		Left unsuccessful	
Scale	*M*	*SD*	*M*	*SD*	*M*	*SD*
Quantitative GPA	2.77	0.87	2.17	0.95	1.24	0.74
Adjusted ACT Math Scores	27.77	3.92	25.77	3.90	24.39	4.23
High School Math Grades	5.50	1.01	5.06	1.08	4.64	1.04
High School Ranks	5.26	1.65	4.72	1.65	4.18	1.71
Lack of Confidence in Academic Ability	3.87	0.49	3.69	0.50	3.70	0.51
Difficulty with Problem Solving	3.95	0.55	3.79	0.60	3.86	0.54
Mathematical Ability	3.46	0.53	3.22	0.84	3.17	0.60
Self-Appraised Abilities	3.15	0.35	3.12	0.36	3.11	0.36

Summary

The results from structural equation model analyses supported the theory that cognitive factors mediate the effects of non-cognitive factors on quantitative GPA. With the measures from the restricted model, a discriminant function analysis yielded distinguishing characteristics among the three groups: admitted to engineering, switched to another major, and left the university unsuccessful. The measures for the latent variable of cognitive factors were higher for the participants who were admitted to engineering and were lower for the participants who left the university unsuccessful.

The interesting finding of the discriminant function analysis was that the participants who left the university unsuccessful reported lower levels of agreement with lack of confidence in academic ability and difficulty with problem solving. Another finding was the similar descriptives for the participants who were admitted to engineering and for those participants who switched to another major at the university. One explanation for this finding could be interest in the field of engineering. The classification table from discriminant function analysis supported this possible explanation because those participants who switched majors were grouped similarly across the three groups. To increase the percentage of students who were admitted to the College of Engineering, cognitive factors, non-cognitive factors, and interest in the field of engineering need to be addressed before entering post-secondary institutions.

CHAPTER V

SUMMARY, CONCLUSIONS, DISCUSSIONS, AND RECOMMENDATIONS

A large amount of empirical research has been conducted on academic achievement with college students. The empirical studies have revealed the significance of high school preparation, more specifically mathematical preparation, for academic success in post-secondary institutions; however, limited research exists for predicting academic success using cognitive and non-cognitive factors (i.e., self-concept, study habits, and inquisitiveness) (French et al., 2005; House, 2000; Shuman et al., 2003). The nature of science, engineering, and mathematics college courses tends to be quantitatively oriented, and calculus tends to serve as the gateway course for academic success within these majors (Gainen, 1995). Conversely, non-cognitive factors significantly contribute to college mathematics achievement beyond standardized test scores or high school ranks.

The purpose of this study was to determine if cognitive factors mediate the effect of non-cognitive factors on quantitative GPA and to determine if these cognitive and non-cognitive factors can predict admission status in engineering education. The study addressed the following research questions: (a) Do cognitive factors (ACT math scores, high school math grades, and high school ranks) mediate the influence of non-cognitive factors on quantitative GPA in the pre-engineering curriculum? and (b) Can cognitive and non-cognitive factors predict engineering admission status?

Summary of Methods

The participants in this study were a sample of 2,276 students who entered Auburn University during the fall semester of 2000 through the fall semester of 2004. Requirements for participation in this study included completion of the College Freshman Survey (Halpin & Halpin, 1996) and at least two quantitative courses in the pre-engineering curriculum at Auburn University.

Exploratory factor analysis. The sample was randomly divided into two databases of comparable size. With one database, an exploratory factor analysis using principal axis factoring with an oblimin rotation was conducted using the following scales from the College Freshman Survey: Math Self-Concept, Self-Appraisal, Perceived Difficulty, Problem-Solving Ability, Need Help, Academic Difficulty, Study Habits, and Academic Self-Concept. The purpose of this factor analysis was to discover the factor structure of the selected items and the correlations between the factors.

Confirmatory factor analysis. With the second database, a confirmatory factor analysis was conducted to determine how the theoretical structure fits with the data and to crossvalidate the factor structures created with the exploratory factor analysis (Meyers et al., 2006).

Structural equation model. After the initial frequencies, descriptives, and bivariate correlations were assessed, a structural equation model was created using AMOS 7.0 to determine the relationship between cognitive and non-cognitive factors and quantitative GPA in the pre-engineering curriculum with 60% of the sample. The exogenous variables were the non-cognitive factors that were created and were confirmed with the factor analyses and the cognitive factors (ACT math scores, mean high school math grades, and high school ranks). Since these data have not been previously analyzed with structural equation modeling, the model created with the 60% sample was applied to the 40% cross-validation sample to confirm the analysis results.

Discriminant function analysis. A discriminant function analysis was conducted using the 60% sample to develop a weighed linear combination to predict group membership (i.e., admitted to engineering, switched to another major at the university, or left the university unsuccessful). The analysis used admission status as the grouping variable and the cognitive and non-cognitive factors as the independent variables. The 40% holdout sample was used to crossvalidate to results with the analyzed 60% sample.

Findings of the Study

The goal of this study was to identify the cognitive and non-cognitive factors that significantly contributed to academic success in quantitative courses within the pre-engineering curriculum. With these factors, this quantitative study sought to differentiate those participants who were admitted to engineering from those participants who either switched to another major at the university or left the university unsuccessful.

The significance contribution of ACT math scores from the structural equation model analysis supports the findings of Besterfield-Sacre et al. (1997), Blumner and Richards (1997), Brown (1994), Buechler (2004), Devens and Walker (2001), French et al. (2005), Heinze et al. (2003), Harackiewicz et al. (2002), House (1995a, 1995b, 2000), House et al. (1996), Lackey et al. (2003), LeBold and Ward (1988), Moller-Wong and Eide (1997), Shuman et al. (2003), Wesley (1994), and Zhang et al. (2004). In addition to ACT math scores, the cognitive factors of high school ranks and high school math grades support the significant findings of Besterfield-Sacre et al., Buechler, Edge and Friedberg

(1984), French et al., Harackiewicz et al., House (2000), House et al., Lackey et al., LeBold and Ward, Moller-Wong and Eide (1997), Sadler and Tai (2001), Shuman et al., Smith and Schumacher (2005), Wilhite et al. (1998), and Zhang et al.

The four non-cognitive variables (lack of confidence in academic ability, mathematical ability, difficulty with problem solving, and self-appraised abilities) from the restricted structural equation model confirm the findings of Besterfield-Sacre et al. (1997), Blumner and Richards (1997), Brown (1994), Brown and Cross (1993), Burtner (2004, 2005), Harackiewicz et al. (2002), House (1993, 1995a, 1995b, 1995c, 2000), Lackey et al. (2003), LeBold and Ward (1988), Litzinger et al. (2005), Nixon and Frost (1990), Shaughnessy et al. (1995) and Shuman et al. (2003).

The structural model analysis revealed that cognitive factors, (ACT math scores, high school math grades, and high school ranks) mediate the effects of non-cognitive factors on the quantitative GPA for the pre-engineering curriculum. Mathematical skills were proven to be the gatekeeper with this sample. In addition, the non-cognitive factors that were found to have a relationship with cognitive factors and were also found to have a significant contribution to the academic success of these participants.

The results from the study conducted by Gilbert (1960), who examined College Board examination scores to predict group membership in engineering retention, suggested that standardized test scores could not be used as the single predictor of success in engineering. In the study conducted by Burtner (2005), non-cognitive factors were used to predict group membership in engineering admission. These results suggested that perceived abilities in mathematics and science could influence students' decision to leave engineering. By using the combination of the cognitive and non-cognitive factors, the discriminant function analysis from the present study correctly classified over 50% of the participants who were admitted to engineering and those participants who left unsuccessful. For the participants who switched to another major, the classification was less accurate and the discriminant function was unable to determine distinguishing factors, which may suggest a lack of interest in the field of engineering that contributes to their decision to switch majors.

As a result of this study, the College of Engineering and K-12 educational systems will become more aware of the effects of cognitive and non-cognitive factors on academic success in pre-engineering. Furthermore, this study has addressed the need for developing mathematical skills and problem-solving abilities at the secondary level so the students will be better prepared for the quantitative courses within the pre-engineering curriculum.

Future Research

In the present study, there was an inability to determine the distinguishing characteristics between the participants who were admitted to engineering and those participants who switched majors at the university. Both of these groups had similar cognitive and non-cognitive skills. Future research is needed to discriminant between the two groups. This research could use a focus group of students who switched majors at the university to determine possible barriers and reasons for their leaving the field of engineering. Based on the topics discussed during the focus group, a survey could be developed to administer to a random sample of students who have switched to other majors at the university since 2000 when the university changed to the semester system.

Another future research topic could be the application of the structural equation model and discriminant function analysis to other southeastern universities with colleges of engineering. This research could determine if the effects of cognitive and non-cognitive factors on the quantitative GPA are unique to this sample or generalizable to other pre-engineering students. Provided the sample of females was sufficient, this research could determine the moderation effect of gender with the cognitive and non-cognitive facts and quantitative GPA.

CHAPTER VI

CURRICULAR IMPLICATIONS

The purpose of this study was to determine if cognitive factors mediate the effect of non-cognitive factors on quantitative GPA and to determine if these cognitive and non-cognitive factors can predict admission status in engineering education. The structural model analysis revealed that cognitive factors (ACT math scores, high school math grades, and high school ranks) mediated the effects of non-cognitive factors (lack of confidence in academic ability, mathematical ability, difficulty with problem solving, and self-appraised abilities) on the quantitative GPA for the pre-engineering curriculum. Furthermore, the non-cognitive skills were found to have a direct relationship with cognitive factors and were also found to have a significant contribution toward the academic success of these participants.

The results of the discriminant function analysis suggested that participants who were admitted to engineering and those participants who left unsuccessful were classified correctly based on the cognitive and non-cognitive factors. For the participants who switched to another major at the university, the classification was less accurate, and the discriminant function was unable to determine distinguishing factors. These results suggest that a lack of interest in the field of engineering may contribute to their decision to switch majors.

With both statistical analyses, structural equation model and discriminant function analysis, all three cognitive measures, lack of confidence in academic ability, and difficulty with problem solving were significant contributors. These results suggest that the need to develop secondary curriculum to increase mathematical proficiency, to increase the self-appraised non-cognitive factors, such as lack of confidence in academic ability and difficulty with problem solving, and to increase the exposure to engineering fields.

Therefore, as a concluding part of this study, a secondary mathematics curriculum was developed to improve mathematical skills and problem-solving abilities. The Mathematics Curriculum for Advanced Mathematical Proficiency (Appendices C, D, E, and F) has the central content of the NCTM Standards (2000) and College Board (2007) recommendations for AP calculus. Within the curriculum, the mathematical concepts are taught within real-world contexts. Each unit has an engineering connection to familiarize the students with the various fields of engineering. The curriculum was devised by consulting with professionals from the fields of naval science, business, construction, and engineering. By integrating various professional fields into the context of each unit, the student will see how mathematical fundamentals integrate throughout all subjects and professions. In addition to key concepts and learning objectives, each curriculum unit contains a summative evaluation. This evaluation serves as a measure of student progress with a culminating performance assessment where the students use their conceptual and procedural knowledge of mathematics to solve an existing problem.

The Mathematics Curriculum for Advanced Mathematical Proficiency will address the following long-term outcomes (see Appendix B for the logic model): (a) To increase the mathematical proficiency of secondary students, (b) To increase the mathematical problem-solving ability of secondary students, and (c) To increase the interest in engineering fields. Implementation will occur over a 4-year period beginning with the first mathematics course, geometry, and phasing in the curriculum with each sequential mathematics course: algebra II, precalculus/trigonometry, and AP calculus.

Context

According to Saylor, Alexander, and Lewis (1981), the common formula for developing a subject-specific curriculum is the use of expert judgment, use of interest and sequence criterion, and use of planning to implement appropriate instruction. Curriculum should be viewed as a plan that encompasses the subject matter, outlines long-term goals and short-term objectives, and provides learning opportunities. Instruction facilitated by the teacher implements the curricular plan. Effective plans assign appropriate weights to the basis of curriculum: society, learners, and knowledge. The values of a society shape the aims of education, but the curriculum planning should be guided by the interests and needs of the learner. Within the curriculum plan, knowledge should be organized to ensure generalizability in future situations. In addition, consideration must be given to the external forces: legal requirements, research, and professional knowledge.

In order to meet the criteria for curriculum development, as prescribed, the five steps for site-specific curriculum development are (a) identify needs, (b) survey available curricular materials, (c) adapt materials to meet the identified needs, (d) develop site-specific materials, and (e) implement new curriculum. When identifying the needs, the data should be collected from the following entities: students, society, knowledge, learning processes, goals, external policies, and resources. When surveying available materials, Saylor et al. (1981) suggested an examination of current textbooks, instructional packages, and local and national curriculum guides. If appropriate materials were available, then one could adapt them to meet the identified needs. If the available materials were not appropriate, then one could develop site-specific materials. After adapting or developing instructional materials, implementation of the new curriculum could occur.

Mathematics curricula are organized in a spiral sequence where concepts and procedures taught in one class are built upon in later classes. Sequential arrangement in a curriculum fosters continuity and integration of learning for a student. The fundamental goal of formal schooling is to develop lifelong learning because 12 years of formal education cannot provide students with all of the skills, knowledge, and attitudes that they will need in the future; however, education can provide a student with the ability to become a lifelong learner for an ever-changing society (Saylor et al., 1981).

Historical Development for Secondary Mathematics Curriculum

When schools developed, the primary goals of the institution were to teach reading and writing skills (Jones & Coxford, 1970). Beginning with the Puritans in Massachusetts, the purpose of education was to convey Christian morality (Litz, 1975). Society believed that by teaching individuals to read and write they would obey the laws of God. With the requirements of the Massachusetts Law of 1642 and Old Deluder Satan Law in 1647, ministers and parents were required to educate the town's youth about the principles of religion and the laws of the colony. The Old Deluder Satan Law required communities of 50 or more families to teach reading and writing. If 100 or more families lived in the town, the law required a Latin Grammar School and hired teacher. The curriculum used at these Latin Grammar Schools was a highly classical one dominated by Latin and Greek. As grammar schools were established throughout the northern states, the focus of the instruction was memorization and recitation of religious catechisms from the *New England Primer* and passages from the *Bible*. These catechisms derived from the beliefs of the Protestant religion (Henson, 2001; Kaestle, 1983; Spring, 2005).

Nineteenth century. The main application of arithmetic was business, and computation skills dominated the content of instruction. During colonial times, the rule method was used for instruction. The students were given ciphering books with a systematic procedure, referred to as a rule, and practice problems to solve (Bidwell & Clason, 1970; Jones & Coxford, 1970). Similar to the rote memorization required for reading, the teachers would repetitiously ask a series of questions, such as “ten and one are how many?,” or give the student a term and expect a definition in return (Jones & Coxford).

During the antebellum period, the purpose of education changed from moral education to citizenship and industry. For instance, children’s stories portrayed completing chores without talking. The teachers used moral persuasion to develop the individual character of the students. The antidotes of Benjamin Franklin’s *Poor Richard’s Almanac* were used in this capacity. Noah Webster’s textbooks integrated the themes of republicanism, Protestantism, and capitalism into the classroom. The philosophical views of John Locke promoted these educational themes. According to Locke, the child’s mind is a blank slate, which means he/she was capable of great moral and intellectual development. This view changed the educational methods from rote memorization to internalizing and understanding the content (Kaestle, 1983). This change in educational philosophy affected the high school mathematics curriculum. When the college requirements increased, algebra and geometry were moved from the college curriculum to the high school, which required students to internalize and apply the concepts instead of memorize and recite them (Jones & Coxford, 1970).

Education is a function of the state according to the Bill of Rights of the U.S. Constitution. State legislatures have the authority to prescribe the curriculum for public schools. At the local level, all state-mandated courses must be offered, but local schools boards have great latitude in supplementing the curriculum. In 1874, the Michigan Supreme Court ruled in Stuart v. S. D. No. 1 of Village of Kalamazoo that local school boards had the responsibility to maintain high schools; however, with this decision, local schools were given implied powers. These implied powers can be used to make specific curricular elements and methods for curriculum implementation (Lunenberg & Ornstein, 2004). Often, curriculum implementation by local school boards differ across a given state because there are differing educational philosophies between school boards, district personnel, and school administrators and different student and teacher populations within a given district. These implemented curricular policies affected the students' experience in mathematics education and thus affected their mathematical performance (Hawkins, Stancavage, & Dossey, 1998).

In 1893, the Committee of Ten rejected the idea for differentiating the curriculum for elementary and secondary schools. The Commission on Reorganization of Secondary Education would reverse this decision in 1918 with their report on Cardinal Principles of Secondary Education. Different abilities among the students were recognized; therefore, a differentiated curriculum was recommended (Saylor et al., 1981). Substantial changes would occur for secondary mathematics curriculum and instruction as the 20th century began.

Twentieth century. In 1920, the National Council of Teachers of Mathematics (NCTM) was founded to keep the interests of mathematics at the top of the education agenda. The first president of NCTM felt that mathematics curriculum should derive from teachers and not educational reformers. With the establishment of NCTM, the struggle between instructional methods and mathematical content was brought to the forefront. In the classroom, when the focus is on content, the pedagogy that focuses on student-centered instruction tends to be restricted. Conversely, if the methods are the focus, the amount of content tends to be limited (Klein, 2003).

In 1925, William Heard Kilpatrick (as cited in Klein, 2003), in his book, *Foundations of Method*, rejected the idea of content-driven instruction. Mathematics should be taught through independent discovery based on the students' needs and interests. Despite his preference for student-centered pedagogy, Kilpatrick felt instruction in algebra and geometry should be discontinued at the high school level. In his report, *The Problem of Mathematics in Secondary Education*, he stated that the content in secondary mathematic should have proven value. Furthermore, he recommended that the traditional high school curriculum involving algebra and geometry was appropriate for a select few individuals. Instruction in basic skills and conceptual knowledge should be differentiated for different students (Commission on the Reorganization of Secondary Education, 1920; Klein). Kilpatrick referred to specialized and elective mathematics courses for 10th-, 11th-, and 12th-grade students who plan to pursue careers in mathematics and sciences. For the other students, their mathematics curriculum should be geared toward vocational training. At the junior high level, the curriculum should teach procedural knowledge and basic arithmetic (Commission on the Reorganization of Secondary Education).

In response to Kilpatrick, the Mathematical Association of America (MAA) published *The Reorganization of Mathematics for Secondary Education* in 1923. This comprehensive report included an extensive survey of secondary curricula, teacher preparation, psychology of learning mathematics, and mathematical applications. MAA recommended curriculum that incorporated algebra for everyone (Klein, 2003). According to the National Committee on Mathematical Requirements (1923), since the majority of students end their formal education years in the ninth grade, the mathematics curriculum should include basic arithmetic with fundamentals of algebra, geometry, and trigonometry. Thus, every student can benefit from understanding the language of algebra and the ability to set up and solve equations based on real-world situations. For those students who remained in high school and had intrinsic mathematical interests, the National Committee recommended elementary calculus for the 12th year in school. The content for this calculus course would be focused on the rate of change and not the superficial.

Changes in the nation's society influenced the shift in content. Up to the 20th century, youth learned their vocational skills from their parents or other adults in the community via apprenticeships (Saylor et al., 1981). As the national economic situation worsened during the Great Depression, the idea emerged to use education as a resource for reconstructing society. Lack of employment caused more students to stay in school;

however, mathematics was unpopular in secondary curriculum (Bidwell & Clason, 1970). It became an elective subject, and enrollment decreased (Jones & Coxford, 1970).

George Counts promoted this social reconstruction philosophy at the 1932 annual meeting of the Progressive Education Association. At this meeting, he attacked capitalism and business control of education in his speech, "Dare Progressive Education Be Progressive?" He suggested that teachers take the lead in this progressive movement and reconstruct society; however, this movement deemphasized the need for rigorous curriculum content in mathematics and sciences (Spring, 2005).

Mathematics gained attention during the 1940s. As young men volunteered for military service, these men needed remediation in basic arithmetic. Officers in the Army and Navy complained about the mathematical deficiencies of new recruits. Based on these complaints, the Life Adjustment Movement emerged. The secondary mathematics curriculum focused on consumer mathematics (i.e., insurance, taxation, and home budgeting). These functional mathematics skills replaced the emphasis on algebra, geometry, and trigonometry. The declining interest in higher level mathematics was evident by enrollment in higher level mathematics courses at the secondary level which had reduced by half since 1910, 56.9% (Klein, 2003).

By the end of the decade, there were advances in technology (i.e., radar, navigation, and atomic energy). These technological advances emphasized the importance of mathematics in the modern society and defeated the social reform movement (Bidwell & Clason, 1970; Klein, 2003). Following World War II, the demand for college-trained personnel grew, which affected college preparatory programs in high school. There were pressures to teach analytic geometry, calculus, and statistics (Jones &

Coxford, 1970). In reality, the mathematics curriculum was unable to keep up with the demand (Bidwell & Cason).

During the Cold War Era, beginning in the 1950s, education was the country's weak link for defense against communism according to Spring (2005). These tensions resulted in a greater emphasis on science and mathematics. The ideology was that by emphasizing science and mathematics the United States could stay technologically ahead of the Soviet Union. In 1957, Russia launched the first satellite, Sputnik I, into space. In response to Sputnik I, Congress passed the National Defense Education Act (NDEA). Title III of the NDEA appropriated nearly $300 million dollars for hiring faculty and purchasing materials for science, mathematics, and foreign language. President Eisenhower wanted to increase the quality of mathematics and science education in order to be competitive in the space and arms race with the Soviet Union (Spring).

In 1960s, "new mathematics" developed as a result of the NDEA. Instead of students learning rote mathematics skills (e.g., add, subtract, multiply, and divide), the students were taught mathematical concepts, such as set theory and functions (Spring, 2005). According to Saylor et al. (1981), these programs were developed by scholars who were content specific. Little emphasis was placed on the needs or interests of the students. Curricula were developed to provide logical explanations for procedural mathematics. For the first time in mathematics education, mathematicians were actively involved in K-12 curriculum development. One of the contributions of the new mathematics movement was the introduction of the calculus course at the high school level (Klein, 2003).

In 1958, the American Mathematical Society established the Science-Mathematics Study Group (SMSG). The group was led by Edward G. Begle from Yale University. During the new mathematics movement, this group created junior and senior high school curricula. These curricula were formal and did not emphasize basic rote skills or application skills. As the curriculum content focus shifted to the abstract, students, parents, and teachers had difficulties with the rigors of the curriculum (Klein, 2003).

Under the Cooperative Research Act, the federal government established the first of several Research and Development Center in 1963. The purpose of these centers was to conduct specialized education research using new programs and instructional strategies (Saylor et al., 1981). President Lyndon Johnson signed the Elementary and Secondary Education Act of 1965 (ESEA). With the passage of ESEA, the federal government used its funds to control educational policies (Spring, 2005). In addition, after the passage of ESEA, there were 30 Research and Development Centers and educational laboratories established by the federal government by the end of 1966. Unfortunately, by the 1970s, the number of these centers and laboratories had declined to 17. These trends marked the back-to-basics (i.e., reading, writing, and arithmetic) movement of the 1970s (Klein, 2003; Saylor et al.).

According to Mann (1976), the mere exposure to calculus did not replace a strong foundation in algebraic fundamentals. Beginning in the mid-1970s, the majority of the states had developed minimum competency exams. These exams assessed basic skills, and half of the states required the students to pass them to earn their high school diploma (Klein, 2003).

The NCTM released *An Agenda for Action* in 1980. This report, which developed later into the national standards, prescribed a new focal point for mathematics education. NCTM recommended problem solving as the focus in mathematics; therefore, skill mastery should not interfere with acquisition of problem-solving skills. Likewise, the report suggested increased calculator use and decreased paper-pencil computations. Most controversial, the NCTM recommended that the role of calculus in the high school curriculum be reevaluated because the new integrated mathematics curriculum did not warrant a specific course in calculus. The students received portions of algebra, geometry, and trigonometry through their integrated textbooks; however, the components were not systematic (Klein, 2003).

As the industrial competition with Japan and West Germany increased, *Nation at Risk,* released by Secretary of Education Terrel Bell and the National Commission on Excellence in Education, in 1983 blamed public schools for the America's failure to compete. The Commission wanted to assess the quality of teaching and learning in the nation's schools, student achievement, and education programs. In addition, the Commission compared the nation's schools to those schools in other advanced nations. This report called for increasing the academic rigor, reforming the curriculum, and improving the quality of the teachers in the school (Henson, 2001; National Commission on Excellence in Education, 1983; Spring, 2005).

The findings of the report stated that there was a rising level of mediocrity, which threatened the future of the nation. Based on their collected data, student achievement (e.g., SAT and NAEP scores) was stagnant since the launch of Sputnik I. Furthermore, the report noted an increasing need for remedial mathematics at post-secondary, business, and military institutions (National Commission on Excellence in Education, 1983). According to Spring (2005), Americans wanted the education system to solve the economic and social problems in society and subsequently close the gap between education and industry.

To address this desire for educational reform, the National Commission on Excellence in Education (1983) wanted to increase the requirements for high school graduation, especially for science and mathematics. Likewise, they demanded a more rigorous curriculum. Science and mathematics curriculum development at the secondary level was targeted to improve performance on standardized achievement tests (e.g., SAT) (Henson, 2001). The National Commission recommended the following implementations, specifically for mathematics curricula: (a) understand geometric and algebraic concepts; (b) understand elementary probability and statistics; (c) apply mathematics to real-life situations; and (d) estimate, measure, and test the accuracy of their calculations (National Commission on Excellence in Education, 1983).

This thought continued when President George Bush presented *Goals 2000*. This plan suggested creating model schools, instituting national standards, establishing a national testing program, and providing incentives for parental choice (Spring, 2005). To facilitate these goals, the Education and Human Resources Division of the National Science Foundation (NSF) developed a series of grants to promote fundamental changes in science and mathematics education. Beginning in 1991, these statewide initiative grants encouraged alignment with the NCTM standards. NSF felt mathematical ideas should be taught using meaningful and real-world situations. The instruction should incorporate inquiry-based learning and problem-solving skills so the students will be effectively and actively engaged students (Klein, 2003).

In 2001, President George W. Bush sponsored the No Child Left Behind (NCLB) Act, which Congress passed in 2002. It mandated that all children had to reach specific levels of academic proficiency in specific subject areas including mathematics by the 2013-2014 academic year. In addition, this law mandated that all children be assessed based on statewide standards in reading, mathematics, and science that would help determine whether a state met its adequate yearly progress goals (NCLB, 2001). This high stakes testing increased the need for mathematical achievement.

The preceding historical developments demonstrated how secondary mathematics curriculum has emerged since the dame kitchen schools. With the primary external force of NCLB, many forget that curriculum development is an evolving process based on a variety of entities (Saylor et al., 1981).

Secondary Mathematics Curriculum

Analyses of the secondary mathematics curricula and textbooks indicated a large scope of content with little in-depth coverage. The recent reform efforts of the NCTM recommended that mathematics curricula cover fewer topics but in greater depth. In addition, they suggested the use of inquiry-based methods and the emphasis on conceptual understanding of the mathematics content. NCLB, passed in 2001, required all states to establish mathematics standards. Resulting from the passage of NCLB, many states have revised their standards and curriculum frameworks and developed a systematic evaluation and modification systems (National Science Board, 2004).

Beginning in 1999, American Association for the Advancement of Science (AAAS) Project 2061 designated teams of mathematics professors and K-12 educators to evaluate textbooks based on the NCTM standards. Of the 12 mathematics textbooks, only four were rated as excellent. In general, the textbooks were deemed inadequate because they tended to teach basic number and geometry skills. These textbook failed to teach higher order thinking skills or to develop the students' reasoning abilities (National Science Board, 2004).

Science curricula and collaborations for K-12 education have integrated science and mathematics using engineering applications. The majority of these curricula were implemented in science classrooms (e.g., Kimmel & Rockland, 2002; Rigby & Harrell, 2005; Schwartz, Regan, & Marshall, 1997). Of the mathematics curricula that incorporate science and technology, the greater part of them was geared toward middle school populations. Furthermore, a minimal number of high school mathematics curricula addressed problem solving and NCTM standards (Klein, 2003). These curricula integrated the content for the algebra-calculus sequence. This integration can prove to be problematic for students and teachers who feel the pressure to pass the high stakes graduation assessments and end-of-course tests (National Science Board, 2004). The pressures of high stakes testing (NCLB, 2001) and standards reform movement in mathematics (NCTM, 2000) demand increased proficiency in mathematics for adequate yearly progress.

According to Shettle et al. (2007), if students take algebra I in ninth grade, then they were more likely to end with algebra II as their highest level of mathematics; however, if the students took geometry in the ninth-grade year, then they were more likely to take calculus before graduating from high school. Thus, a mathematics curriculum at the high school level should be restructured to include the skills to master college-level calculus.

Needs Assessment

A major source of student achievement and performance is the National Assessment of Educational Progress (NAEP). Established in 1969, the NAEP measures the nation's educational progress by routinely administering subject-area assessments to a representative sample of 4th-, 8th-, and 12th-grade students. With scientifically selected samples, reading, mathematics, social studies, and science are assessed by performance tasks and multiple-choice questions (Saylor et al., 1981).

The mathematics section of the NAEP contains a combination of multiple-choice (54%), short constructed-response (40%), and extended constructed-response (6%) items. The constructed-response questions assess the students' ability to reason and communicate mathematical knowledge. The NAEP allows the use of calculators, rulers, protractors, and manipulatives (e.g., geometric shapes, three-dimensional models, and spinners). No one student completes the entire assessment. A portion of the assessment is administered to each student. The data are combined across students to provide estimates of mathematical achievement for 4th-, 8th-, and 12th-grade students. The estimates are disaggregated by gender and ethnic group (Mitchell, Hawkins, Jakwerth, Stancavage, & Dossey, 1999).

NAEP reports provide composite mathematics scales on a 3-point scale (i.e., basic, proficient, and advanced). Basic level is defined as partial mastery of prerequisite knowledge and skills expected for the grade level. Proficient level is defined as solid academic performance for grade level, which includes the ability to apply conceptual knowledge to real-world situations and to use analytical skills within the mathematics content. At the advanced level, the mathematical performance is considered superior. The NAEP mathematics assessment is divided into five content strands: (a) number sense, properties, and operations; (b) measurement; (c) geometry and spatial sense; (d) data analysis, statistics, and probability; and (e) algebra and functions (Mitchell, Hawkins, Jakwerth et al., 1999).

Number Sense, Properties, and Operations

The content strand focuses on mathematical operations using whole numbers, fractions, decimals, integers, and rational numbers. In addition, students are expected to apply their understanding to real-world situations. For the Grade 12 level, the content strand includes real and complex numbers. When asked to evaluate expressions for odd/even, 92% of the 12th-grade students answered at least one entry correctly. For students who had taken algebra II, 94% of them answered at least one entry correctly. Likewise, 91% of the students who had taken calculus as their highest level of mathematics answered at least one entry correctly. When asked to solve a rate versus time problem, which required application skills, 49% of the students responded correctly. For students who took algebra II as their highest level of mathematics, 48% of them responded correctly, but 65% of the students who took calculus as their highest level answered correctly. When the 12th-grade students were asked to compute a percent increase, which required problem-solving skills, 56% of the 12th-grade students answered incorrectly (Mitchell, Hawkins, Jakwerth et al., 1999).

At the Grade 12 level, 33% of the students who took calculus I as their highest level of mathematics responded incorrectly as opposed to 57% of the students who took algebra II as the highest level. Based on these results, the majority of the students were successful when solving explicit computational problems; however, the 12th-grade students tended to experience difficulties when they were asked to respond to problems involving multiple steps, application of conceptual knowledge, and problem-solving skills. For number sense, in the 1996 NAEP, 12th-grade students who were enrolled in calculus had an average score of 338 from a range of 0 to 500, and the average score for those 12th-grade students who ended their mathematics sequence with algebra II was 304 (Mitchell, Hawkins, Jakwerth et al., 1999).

Measurement

The content strand involves (a) units of measurement; (b) measurement instruments; (c) perimeter, area, and volume; and (d) estimation of measurements. The questions involve complex application of volume and surface area. In addition, there are questions involving proportions with maps and scale drawings. When 12th-grade students were asked to recognize the best unit of measurement, 87% of the students responded correctly. There was not a statistical difference among the mathematics courses. In contrast, the students were asked to use a protractor to draw a 235° arc on a circle, 25% of the students responded correctly with a maximum 5° margin of error. When examining the highest level of mathematics, 24% of those students who took algebra II responded correctly, but 56% of those students who took calculus I responded correctly. There was a 32% difference between the two mathematics courses. The differences in mathematical abilities were evident when the 12th-grade students were asked to find the volume of a cylinder. The 12th-grade students who took calculus I answered with 56% accuracy as opposed to 31% of the students who took algebra II as their highest level of mathematics (Mitchell, Hawkins, Jakwerth et al., 1999).

Parallel results were seen when the students were asked to find the perimeter of a quadrilateral, to use a ruler to find the circumference of a circle, and to compare the area of two shapes. Moreover, students who took more advanced mathematics courses tended to perform better compared to those students in less advanced mathematics (i.e., calculus I versus algebra II). In the measurement strand, for students enrolled in calculus, the average score was 337 from a range of 0 to 500; however, the students who were enrolled in algebra II had an average score of 305 on the 1996 NAEP (Mitchell, Hawkins, Jakwerth et al., 1999).

Geometry and Spatial Sense

This content strand concentrates on the conceptual understandings of geometry figures and their properties. At Grade 12 level, the strand involves transformational geometry and application of proportional thinking and geometric formulas. When 12th-grade students were asked to use similar triangles, 37% of the students answered correctly. Sixty-two percent of the students who took calculus responded accurately, and only 32% of the students who took algebra II responded accurately. Furthermore, when the 12th-grade students were asked to draw a parallelogram with perpendicular diagonals, 18% of them performed the task correctly. For the students who took calculus, 56% of them responded correctly; however, only 18% of the students who took algebra II responded correctly. Similar accuracy levels were seen when the 12th-grade students were asked to use a protractor to draw perpendicular lines and measure angles and to describe the geometric process for finding the center of a disk (Mitchell, Hawkins, Jakwerth et al., 1999).

When the 12th-grade students were asked to assemble pieces to form a shape that was not a square, 58% of the 12th-grade students performed the task correctly. Students who took calculus responded with 65% accuracy compared to 59% accuracy for the students who took algebra II. Most of the questions in this strand required the students to draw or explain a response and to apply their knowledge of geometric properties. These types of questions were difficult for the 12th-grade students. Students in the more advanced mathematics tend to perform better than those students in the less advanced mathematics courses. There was a 35-point difference in average geometry strand scores for those students who took calculus and those students who took algebra II on the 1996 NAEP (Mitchell, Hawkins, Jakwerth et al., 1999).

Data Analysis, Statistics, and Probability

The content strand focuses on the ability to collect, organize, read, represent, and interpret data. For the Grade 12 level, the questions require the use of statistical techniques and the application of probability to dependent and independent events. When 12th-grade students were asked to use data from a chart to make a decision and explain their rationale, 67% of the 12th-grade students answered correctly. There was not a substantial difference between students in more advanced mathematics courses and those students in the less advanced mathematics courses (Mitchell, Hawkins, Jakwerth et al., 1999).

Likewise, when 12th-grade students were asked to use data in a table to compute hourly wages and determine when the wage rate changed, only 13% of the 12th-grade students responded correctly. Twenty-five percent of the students who took calculus responded correctly compared to 15% of the students who took algebra II as their highest level of mathematics course. Comparable results were seen when 12th-grade students were asked to compare means and medians. Only 4% of the responses were rated at least satisfactory on the 4-point scale (i.e., extended, satisfactory, partial, and minimal). Sixteen percent of the responses by students who took calculus were rated at least satisfactory as opposed to 2% of the responses by students who stopped their mathematics coursework with algebra II. When the students were asked to compare probabilities, 28% of the 12th-grade students answered correctly with at least a partial explanation. There was a 30% difference between students who took more advanced mathematics course and those students who took less advanced mathematics, 58% and 28%, respectively (Mitchell, Hawkins, Jakwerth et al., 1999).

Consistent with the results with the other content strands, the students tended to be successful with the explicit questions pertaining to graphs, charts, and tables. When the students were asked to compute and reason calculations based on displayed data, the students' performance indicated those types of questions were more difficult. The more mathematics courses a student took the better their mathematical ability; however, problem solving and multiple steps requiring answers from previous steps were challenging for the advanced students. In 1996, students who took calculus had an average score of 333, from a range of 0 to 500, on the data analysis and probability strand. The average score for those students who ended their mathematics courses with algebra II was 307 (Mitchell, Hawkins, Jakwerth et al., 1999).

Algebra and Functions

The content strand focuses on algebraic notation and the ability to solve equations. At Grade 12 level, the strand involves the use of functions to represent and describe relationships. For the 12th-grade students, when asked to identify a graph of a specific function, 20% of the students answered correctly. When examined by the highest course taken in the algebra-calculus sequence, 17% of the students, who responded that algebra II was their highest mathematics course completed, answered the question correctly, and 55% of the students, who responded that calculus was their highest level of mathematics, answered the question correctly. Similar results were seen with solving a pair of equations and using trigonometric identities (Mitchell, Hawkins, Jakwerth et al., 1999).

On the other hand, when 12th-grade students were given an extended constructed-response question to assess the problem-solving ability of the students, the results were not statistically significant. When asked to describe the pattern of squares in a particular figure, only 4% of all 12th-grade students earned at least satisfactory on a 5-point scale (i.e., extended, satisfactory, partial, minimal, and incorrect). For students who had taken either pre-calculus or calculus, the percentage who earned at least satisfactory was 18% and 10%, respectively. Four percent of the students who scored at least satisfactory responded that algebra II was their highest level of mathematics. This question lends support to the idea that all students are challenged when asked to apply their problem-solving skills and communicate their ideas in writing. The difference between the average strand scores of those students who were enrolled in calculus and those students who took algebra II was 41 points (Mitchell, Hawkins, Jakwerth et al., 1999).

According to Grigg, Donahue, and Dion (2007), 61% of high school seniors performed at or above the basic level on the 2005 NAEP, and only 23% of them performed at or above the proficient level. As concluded by the 1996 NAEP data, students who took higher level mathematics courses were more likely to perform better on the NAEP (i.e., 182 for calculus and 143 for algebra II from a range of 0 to 300). Students were able to identify a solution or compute values when all information was given in the mathematics problem. The performance of these students indicated the students have the ability to make direct applications of concepts or procedures (e.g., using the Pythagorean Theorem to determine the length of a hypotenuse), but they are unable to implicitly apply their knowledge with multiple steps.

Successful mathematics achievement requires the completion of more advanced mathematics courses. Results from the NAEP data revealed that significant differences existed between students who took calculus I and those students with algebra II as their highest level of mathematics. Students who took one more high school mathematics course increased their average by 18 points, approximately 6%, on the 1996 NAEP. For those students with two additional mathematics courses, the average increase was 33 points (approximately 10%) (Mitchell, Hawkins, Jakwerth et al., 1999).

This trend has continued according to Perie, Moran, Lutkus, and Tirre (2005) and Shettle et al. (2007), and the average point difference has increased. The average mathematics score for those student who took calculus was 336 from a range of 0 to 500, and, for those students with algebra II as their highest level of mathematics courses completed, the average score was 310 (Perie et al.). This 26-point gap widened further in 2005. The average score for calculus students was 192 from a range of 0 to 300 and for algebra II students was 142. Despite the scale's maximum range changing from 500 to 300, a 50-point difference existed for students with 2 more years of advanced mathematics preparation (Shettle et al.).

In 2005, 89% of the students who performed at the advance level had calculus as their highest course completed, and less than 1% of the students who reported algebra II as their highest mathematics course performed at the advance level (Shettle et al., 2007). According to Mitchell, Hawkins, Jakwerth et al. (1999), lower performing students may select or be assigned to less advanced mathematics courses, and the mathematics course may not be providing them with challenging opportunities. Therefore, the likelihood of their ending their mathematics courses earlier in their high school career increases. By taking algebra I during the eighth-grade year, the likelihood increases for students who take more mathematics courses and more advanced coursework. Despite the percentage of students taking algebra I during their eighth-grade year increasing (Mitchell, Hawkins, Jakwerth et al., 1999), the percentage of 12th-grade students who end their mathematics courses with algebra II has remained unchanged. In 2004, 53% of the 12th-grade students reported that algebra II was their highest level of mathematics courses (Perie et al., 2005).

This unchanged percentage reflects curriculum concerns in advanced mathematics courses. At the high school level, the majority of the schools require 3 years of mathematics, referred to as midlevel curriculum. Since 1990, the average number of required mathematics courses has increased from 3.2 to 3.8. Only 10% of the high school graduates in 2005 participated in a rigorous curriculum level where 4 years of mathematics was required. The traditional sequence of mathematics courses at the high school level is algebra I, geometry, algebra II, pre-calculus, and calculus. Based on this sequence, for a student who took algebra I in eighth grade and continued to take courses until his or her 12th-grade year, the highest level of mathematics would be calculus. Thus, it is likely that a graduating senior would not be involved in formal mathematics courses for at least one year (Shettle et al., 2007). The lack of formal exposure affects students' overall mathematical ability (Mitchell, Hawkins, Jakwerth et al., 1999).

Mathematical Problem-Solving Ability

According to Mayer (2003), mathematical problem solving includes three components: cognitive, process, and directed. Therefore, problems, which contain mathematical content that involves problem solving, require the individual to use his or her cognitive abilities, to apply his or her mental computations to a mental representation, and to direct the activities to achieve an outcome. In mathematical problem solving, there are two types of problems: routine and non-routine. Routine problems are exercises where the individual immediately sees the solution procedure (e.g., 2 X 2). On the other hand, with non-routine problems, the solution procedures are not obvious to the individual.

Mathematical problem solving is composed of four interdependent cognitive processes: translating, integrating, planning, and executing. When an individual reads a mathematical word problem, he or she translates or paraphrases the sentences into a mental representation. This process employs semantic and linguistic knowledge. The process of integrating involves schematic or conceptual knowledge because the individual builds a mental model of the word problem. During the planning process, the individual devises a plan for how to solve the word problem, which utilizes strategic knowledge. After representing the word problem, building a model, and devising a plan, in the executing process, the individual executes out the strategic plan using his or her procedural knowledge (Mayer, 2003).

Each of these cognitive processes requires the application of prior knowledge and experience with mathematical concepts and procedures. Often, the lack of mathematical problem-solving ability causes the individual to select the numbers from the word problem and conduct rote procedures based on key word phrases. With instruction, individuals can recognize structural similarities among word problems and solve them effectively. Mayer (2003) noted that computational fluency aids mathematical problem solving. If the individual can complete computations automatically, his or her cognitive resources can be devoted to the four cognitive processes of mathematical problem solving.

Mitchell, Hawkins, Stancavage et al. (1999) conducted the study of mathematics-in-context, referred to as the theme study. The purpose of the theme study was to assess the students' problem-solving abilities within real-life contexts and to determine how the students make connections across content areas of mathematics. The participants were 4th-, 8th-, and 12th-grade students who took the 1996 NAEP mathematics assessment. For Grade 12, there were 3,860 participants who represented 196 schools. Each participant was given an assessment booklet with a theme block, which contained grade-appropriate real-life scenarios, and a grade-appropriate block of mathematics questions. This instrument was administered separately from the main 1996 mathematics assessment.

The participants were given 30 minutes to complete the theme block and 15 minutes to complete the block of mathematics questions. The 12th-grade participants were given seven questions about buying a car (two multiple-choice and five constructed-response items). With these participants, at least 90% of the items were attempted; however, the researchers found that the majority of the students tended to have difficulties with complex multiple-step problems (Mitchell, Hawkins, Stancavage et al., 1999).

Forty-one percent of the participants responded correctly to the Buying A Car Theme block. When the participants were asked to find the amount of the down payment, 82% of them answered correctly. Similar results were seen with finding the total amount paid for the car (83%) and finding the difference between total amount paid and price (80%). All three of these questions derived from the number sense, properties, and operations content strand and required procedural knowledge (Mitchell, Hawkins, Stancavage et al., 1999).

When participants were asked to find the amount to be financed, which required multiple steps, only 34% of the participants provided a complete and correct response. When asked to use a formula to find the total cost of the car, 23% of the participants scored at least satisfactory on a 5-point scale (i.e., extended, satisfactory, partial, minimal, and incorrect). Similar percentages were seen with finding the amount saved if leased (27%) and comparing the price of leasing and the price of buying (16%). When questions required conceptual or procedural knowledge with minimum steps and straightforward calculations, the high percentage of participants responded correctly, but, when the question required multiple steps and/or problem-solving ability, the percentage correct dramatically reduced. The researchers noted that the participants appeared to have difficulties when they were required to isolate the information needed to solve the problem. Extraneous information seemed to complicate the solving of the word problems (Mitchell, Hawkins, Stancavage et al., 1999).

Another study conducted by Mitchell, Hawkins, Stancavage et al. (1999) was the study of students taking advanced courses in mathematics, referred to as the advanced study. The purpose of the advanced study was to assess the level of mathematical proficiency, primarily in the content strand of algebra and functions, of the students who were taking or had taken advanced mathematics courses (e.g., pre-calculus or calculus for Grade 12). The participants were 2,965 12th-grade students which represented 207 schools. The format of the instrument was similar to the Theme Study with a block of mathematics questions and a theme block. The 12th-grade assessment contained 7 multiple-choice, 10 short constructed-responses, and 5 extended constructed-response items. For Grade 12, 30% of the items were answered correctly.

When asked to use a linear function, 20% of the participants provided a correct response with a complete explanation of their process. When asked to compare the volumes of three pyramids, only 10% of the participants' responses were rated at least satisfactory on a 5-point scale (i.e., extended, satisfactory, partial, minimal, and incorrect). Mitchell, Hawkins, Stancavage et al. (1999) hypothesized that performance on items which contained content that the participants had not studied since 9th- or 10th-grade years tended to be reduced because the participants lacked the continuous exposure to the mathematical content. Therefore, in addition to the inability to solve mathematical problems with two or more successive steps, the participants appeared to be unable to maintain and generalize mathematical concepts.

According to the NAEP data, in 1999, only 8% of all 17-year-old students across the nation had the ability to solve multiple-step word problems using reasoning skills (Campbell et al., 2000). In 2004, 7% of the 12th-grade students performed at the level which requires students to apply reasoning skills to multiple-step problems. This percentage has not changed since 1973 despite significant increases with the percentages for 4th- and 8th-grade students (Perie et al., 2005).

According to Perie et al. (2005), 8th-grade students have significantly increased their performance on the NAEP mathematics assessment, which ranged from 0 to 500, from 1973 (266) to 2004 (281); however, 12th-grade performance has remained stagnant from 1973 (304) to 2004 (307). After further examination, 12th-grade students who fell in the 50th percentile and lower significantly increased their mathematics performance, but the students in the 75th and 90th percentiles did not significantly improve their performance (from 325 to 330 and from 345 to 345, respectively).

Proposed Strategy

Goal #1

To increase the mathematical proficiency of secondary students.

Objectives (Outcome)

1. To increase mathematical proficiency levels across implementation years and across mathematics courses based on benchmark examinations.
2. To increase AP calculus scores across implementation years.
3. To increase graduation exit examination mathematics subtest scores across implementation years.

Goal #2

To increase the mathematical problem-solving ability of secondary students.

Objectives (Outcome)

1. To increase mathematical problem-solving abilities across implementation years and across grade levels.

Goal #3

To increase the interest in engineering fields.

Objectives (Outcome)

1. To increase the number of students who intend to major in engineering fields as they enter post-secondary institutions.
2. To increase the number of students who are admitted to a school of engineering.
3. To increase the number of students who graduate with a bachelor's degree in engineering.

Method

Participants

The selected participants will be all high school students over a 4-year period within the school district selected as the implementation site. The school district, with a total enrollment of 12,000, includes three high schools (Grades 9 through 12) with an approximate enrollment of 3,490. The number of students increases an average of 2% each academic year. The gender classification is 48% male and 52% female. The racial makeup of the district is 54% White, 41% Black, and 5% who classify themselves as belonging to other racial groups. Eight percent of the students receive special education services. Fifty-nine percent of the students are eligible for free or reduced meals.

Intervention Activities

Description: Curriculum. The geometry curriculum consists of six units: (a) land and water navigation, (b) horticulture/landscape design, (c) bridge building, (d) adaptive devices, (e) simple and complex machines, and (f) friction. The navigation unit covers the geometric concepts related to triangles and parallel lines. The horticulture unit covers the properties and theorems associated with circles. In the bridge building unit, the content includes three-dimensional shapes. The adaptive devices unit covers symmetry and transformations. For the simple and complex machines unit, the content includes Euclid's axioms and postulates. The friction unit focuses on the geometric concept of surface area.

The algebra II curriculum consists of five units: (a) thermodynamics, (b) viral diseases, (c) HVAC systems, (d) cellular respiration, and (e) pipeline design. The thermodynamics unit covers addition of functions, inequalities, and transformation of functions. The viral diseases unit covers linear functions, systems of equations, and tree diagrams. The HVAC systems unit includes area and volume. For the cellular respiration unit, the content includes additive growth, multiplicative growth, and exponential equations. The pipeline design unit focuses on the geometric concepts of slope and rate of change.

The pre-calculus/trigonometry curriculum consists of seven units: (a) business plan, (b) electrical circuits, (c) wave motion, (d) aeronautical navigation, (e) optics, (f) introduction to statistics, and (g) dynamic systems. The business plan unit covers logarithms, bases, and logarithmic functions. The electrical circuits unit covers the properties and applications of polynomials. In the wave motion unit, the content includes the trigonometric functions. The aeronautical navigation unit covers coordinate systems and vectors. The optics unit focuses on analytic geometry. In the introduction to statistics unit, the content includes the binomial theorem. The dynamic systems unit covers change with discrete dynamical systems, including constant, linear, and proportional change.

The AP calculus curriculum consists of five units: (a) water supply, (b) market growth, (c) amusement park design, (d) rocket design, and (e) loglinear analysis. The water supply unit covers local linearity. The market growth unit covers functions and limits. The amusement park design unit includes the derivative and applications of differentiation. For the rocket design unit, the content includes the integral and applications of integration. The loglinear analysis unit focuses on transcendental functions. (See Appendix C for specific geometry curriculum unit outlines, Appendix D for algebra II curriculum unit outlines, Appendix E for pre-calculus/trigonometry curriculum unit outlines, and Appendix F for AP calculus curriculum unit outlines.)

Description: Workshops. During the year prior to implementation, the evaluator and teachers will use the curriculum units to develop instructional lessons and incorporate applicable lessons from their previous lesson materials. At each professional development workshop where lesson plans were developed, a lesson plan design rating system will be conducted (Appendix G). This rating system was adapted for this application using the Inside the Classroom: Observation and Analytic Protocol (Horizon Research, 2000). A team of three teachers who were not involved in the development of the lesson plan will review the lesson's design and content independently. Based on their evaluations and recommendations, the lesson plan will be revised or submitted to the curriculum unit.

At subsequent professional development workshops, the evaluator will work with the high school teachers to develop two benchmark examinations, midterm and final examinations, for the geometry, algebra II, pre-calculus/trigonometry, and AP calculus courses. The examinations will contain items that will be representative of the expectation instructional content for that time period. As a summative evaluation, a benchmark examination, which will be a multiple-choice format, will be given every 18 weeks to assess mathematical proficiency based on course content and performance standards.

In addition to the lesson plans and benchmark examinations, the high school teacher staff will create the mathematical problem-solving examination, which will be administered at the end of each course. The items for the mathematical problem-solving examination will be written, peer reviewed, field-tested, and data reviewed prior to placement on the final form. The examination will consist of four tasks (one each from statistics and probability; algebraic relationships; measurement; and geometry).

High school mathematics teachers will score the examinations after attending 2 days of training. At the training workshops, the evaluators will work on the four sample tasks at their grade level. When a consensus is reached among the scoring panel, these criteria responses will be used to illustrate the scoring guide and the variety of possible solutions for each task during training and scoring. After further training with the criteria papers, each rater will qualify to score the examinations by accurately scoring a packet of examinations. (See Appendix H for the scoring rubric.)

At the conclusion of each professional development workshop, all participants will complete an exit survey to determine the effectiveness of the session and determine future professional development needs. (See Appendix I.) The exit survey was developed using a variety of preexisting instruments. Questions regarding instructional and student assessment methods were devised from the National Survey of Science and Mathematics Education (Westat, 2000). The areas of future professional development needs were based on the Local Systemic Change: Principal Questionnaire (Horizon Research, 2006). The items, which relate the importance for the skill to student success in mathematics, were collected from the Mathematics Teacher Questionnaire: Main Survey (TIMSS Study Center, 1998).

Procedure: Implementation. The geometry curriculum will be implemented during Year 1 at each high school in the school district. The teachers will be provided with curriculum materials and instruction during August at teacher pre-service meetings. One hundred eighty lessons from the Mathematics Curriculum for Advanced Mathematical Proficiency will be taught in 55-minute sessions from August to May. When students are absent, they will receive makeup lessons. Each teacher will document that the lesson was taught in his or her daily lesson plan book. These daily lesson plans will be turned into the school administrative team for review.

Beginning in Year 2, the geometry curriculum will continue with the next freshman class, and the algebra II curriculum will be implemented. In Year 3, the geometry and algebra II curricula will continue, and the pre-calculus/trigonometry curriculum will be implemented. During Year 4, utilization of the geometry, algebra II, and pre-calculus/trigonometry curricula will continue, and the AP calculus curriculum will be implemented.

Procedure: Data collection. For each implementation year, the school administrative staff will gather the graduation exit examination mathematics subtest and AP calculus examination scores. In addition, the guidance office staff will collect the number of students who intended to major in engineering, the number of students who were admitted to a school of engineering, and the number of students who earned a bachelor's degree in an engineering field by contacting the former students.

Process Evaluation

Reach. Reach is the extent to which the targeted populations received the scheduled intervention dosages. The students' participation in the curriculum activities will be assessed using the teachers' daily attendance record.

Dosage. The geometry curriculum will consist of 180 lessons at 55 minutes each. The algebra II curriculum will consist of 180 lessons at 55 minutes each. The pre-calculus/trigonometry curriculum will consist of 180 lessons at 55 minutes each. The AP calculus curriculum will consist of 180 lessons at 55 minutes each. The lessons will be taught once a day for 36 weeks during the scheduled mathematics class time block.

Fidelity. With the weekly informal observation forms, school personnel will monitor the implementation process in the classroom. (See Appendix J.) One of the following people will conduct these observations: school principal, assistant principal, curriculum director, or assistant curriculum director. A professional development workshop will be conducted to train the observers with the weekly informal observation form and behavioral checklist. Sample videos of classroom instruction will be utilized during the training workshop. After direct instruction and guided practice, independent practice will occur until the interrater reliability among the observers is consistent.

Formative evaluation. A formative evaluation will be conducted to assess the attitudes and instructional methods of the teachers throughout the implementation process. A demographic survey will collect information regarding education level, certification areas, and years of experience in public education. Qualitative interviews with the implementing teachers and other faculty members will ascertain their perceptions and gather feedback for program improvements. The series of interviews will be conducted during pre-planning, midterm, end of the course, and post-planning. Since adults are more likely to reject the new knowledge that contradicts their beliefs, the information gathered during these interviews will evaluate existing knowledge, beliefs, and motivations and will determine the extent to which the implementing teachers have ownership in the curriculum implementation process (Klingner, Ahwee, Pilonieta, & Menendez, 2003).

Outcome Evaluation

Participants

Comparison. During the academic year prior to implementation, the students who are enrolled in geometry, which will be primarily ninth- and tenth-grade students, will be assessed using the two benchmark examinations and the mathematical problem-solving examination. These grade ahead comparisons will serve as baseline data for which to compare the mathematical proficiency and mathematical problem-solving ability of the implementation group. In addition, baseline information will be collected from the school's administrative staff regarding the scores from AP calculus examinations and the scores from the graduation exit examination mathematics subtest. Baseline information will be collected regarding the number of students during Year 0 who plan to major in engineering and the number of previous students who earned a bachelor's degree in an engineering field.

Intervention. Beginning with the first year of implementation, the students who are enrolled in geometry will be assessed using the two benchmark examinations and the mathematical problem-solving examination. In the second year of implementation, the students who are enrolled in algebra II will be assessed using the benchmark and mathematical problem-solving examinations. During the third year, the students who are enrolled in pre-calculus/trigonometry will complete the prescribed assessments and the graduation exit examination mathematics subtest. Lastly, in the fourth year of implementation, the students who are enrolled in AP calculus will complete the benchmark examinations, the mathematical problem-solving examination, and the AP calculus examination.

Design

Objective 1.1. With the scores from the midterm and final benchmark examinations, a 4 X 2 analysis of variance (ANOVA) will be conducted to determine if mathematical proficiency levels changed across implementation years and across mathematics courses. An intervention sample of students who begin the geometry-calculus sequence in Year 1 will be tracked through Year 4 to assess mathematical proficiency with the comparison group. In addition, an intervention sample of students who begin the geometry-calculus sequence in Year 2, in Year 3, and in Year 4 will be compared with the comparison sample of students. With a profile analysis, the repeated measure analysis will determine group differences and longitudinal trends between the intervention and comparison groups.

Objectives 1.2 and 1.3. To analyze the long-term outcomes for the Mathematics Curriculum for Advanced Mathematical Proficiency, with the scores from the AP calculus examinations and the scores from the graduation exit examination mathematics subtests, longitudinal trends will be graphed using the percentage of passing scores and the average score with both examinations across the implementation years.

Objective 2.1. After the initial descriptives are assessed, a repeated measure ANOVA with one within-subject factor (time) and two between-subject factors (group and grade level) will be conducted to determine if mathematical problem-solving abilities have changed across implementation years and across grade level and group. An intervention sample of students who begin the geometry-calculus sequence in Year 1, in Year 2, Year 3, and Year 4 will be compared to a comparison sample of students.

Objectives 3.1, 3.2, and 3.3. A frequency count of the number of students who intend to major in engineering at high school graduation, the number of students who were admitted to a school of engineering, and the number of students who earn a bachelor's degree in an engineering field will be assessed. Based on these frequency counts, a chi-square non-parametric analysis will be conducted to determine if the observed numbers differ from the expected numbers across implementation years.

Expected Findings

The expected findings will include increased mathematical proficiency and increased mathematical problem-solving ability as the curriculum was implemented. The evaluator will expect to see increased scores on the graduation exit examination mathematics subtest and on the AP calculus examination. In addition, the evaluator will expect the numbers of students who pursue engineering majors, numbers of students who are admitted to engineering, and numbers of students who graduate with a bachelor's degree in an engineering field to increase.

The findings of the program evaluation plan will be reported to the school faculty each semester as a formative report and each pre-service faculty meeting during the implementation period as a summative report. Once a semester, the evaluator will meet with the superintendent individually and with the local school board during a caucus meeting to discuss the results. Afterwards, an annual summative report will be presented at a public school board meeting.

REFERENCES

Anthony, J. M., Hagedoorn, A. H., & Motlagh, B. S. (2001). Innovative approaches for teaching calculus to engineering students. Paper presented at the ASEE Annual Conference, Albuquerque, NM.

Baron, J., & Norman, M. F. (1992). SATs, achievement tests, and high-school class rank as predictors of college performance. *Educational and Psychological Measurement, 52*, 1047-1055.

Besterfield-Sacre, M., Atman, C. J., & Shuman, L. J. (1997). Characteristics of freshman engineering students: Models for determining student attrition in engineering. *Journal of Engineering Education, 86*, 139-148.

Betz, N. E. (1987). Use of discriminant analysis in counseling psychology research. *Journal of Counseling Psychology, 34*, 393-403.

Bidwell, J. K., & Clason, R. G. (Eds.). (1970). *Readings in the history of mathematics education*. Washington, DC: National Council of Teachers of Mathematics.

Blumner, H. N., & Richards, H. C. (1997). Study habits and academic achievement of engineering students. *Journal of Engineering Education, 86*, 125-132.

Brown, N. W. (1994). Cognitive, interest, and personality variables predicting first-semester GPA. *Psychological Reports, 74*, 605-606.

Brown, N. W., & Cross, Jr., E. J. (1993). Retention in engineering and personality. *Educational and Psychological Measurement, 53*, 661-671.

Buechler, D. N. (2004). *Mathematical background versus success in electrical engineering*. Paper presented at the ASEE Annual Conference, Salt Lake City, UT.

Burtner, J. (2004). *Critical-to-quality factors associated with engineering student persistence: The influence of freshman attitudes*. Paper presented at the Frontiers In Engineering Conference, Savannah, GA.

Burtner, J. (2005). The use of discriminant analysis to investigate the influence of non-cognitive factors on engineering school persistence. *Journal of Engineering Education, 94*, 335-338.

Burton, M. B. (1989). The effect of prior calculus experience on "introductory" college calculus. *The American Mathematical Monthly, 96,* 350-354.

Campbell, C. M., Hombo, C. M., & Mazzeo, J. (2000). *NAEP 1999 trends in academic progress: Three decades of student performance*. Washington, DC: U.S. Department of Education, Office of Education Research and Improvement, National Center for Education Statistics. Retrieved January 20, 2005 from http://nces.ed.gov/pubsearch/pubsinfo.asp?pubid=2000469.

College Board. (2007). *Calculus: Calculus AB calculus BC course descriptions*. New York: Advanced Placement Program National Office. Retrieved May 14, 2007 from http://www.collegeboard.com/prod_downloads/ap/students/calculus/ap-cd-calc-0708.pdf.

Commission on the Reorganization of Secondary Education. (1920). The problem of mathematics in secondary education. Washington DC: Department of the Interior, Bureau of Education. In J. K. Bidwell, & R. G. Clason (Eds.) (1970), *Readings in* *the history of mathematics education*. Washington, DC: National Council of Teachers of Mathematics.

Devens, P. E., & Walker, T. D. (2001). Freshman engineering student success indicators. Paper presented at the ASEE Annual Conference, Albuquerque, NM.

Edge, O. P., & Friedberg, S. H. (1984). Factors affecting achievement in the first course in calculus. *Journal of Experimental Education, 52*, 136-140.

Felder, R. M., Forrest, K. D., Baker-Ward, L., Dietz, E. J., & Mohr, P. H. (1993). A longitudinal study of engineering student performance and retention: I. Success and failure in the introductory course. *Journal of Engineering Education, 82*, 15-21.

Ferguson, G. A., & Takane, Y. (1989). *Statistical analysis in psychology and education* (6th ed.). New York: McGraw-Hill Publishing Company.

French, B. F., Immekus, J. C., & Oakes, W. C. (2005). An examination of indicators of engineering students' success and persistence. *Journal of Engineering Education, 94*, 419-425.

Gainen, J. (1995). Barrier to success in quantitative gatekeeper course. In J. Gainen, & E. W. Willemsen (Eds.), Fostering student success in quantitative gateway course. *New Directions for Teaching and Learning, 61*, 1-3.

Gainen, J., & Willemsen, E. W. (Eds.). (1995). Fostering student success in quantitative gateway course. *New Directions for Teaching and Learning, 61*, 1-3.

Gilbert, A. C. F. (1960). Predicting graduation from an engineering school. *Journal of Psychological Studies, 11*, 229-231.

Grigg, W., Donahue, P., & Dion, G. (2007). *The nation's report card: 12th-grade reading and mathematics 2005.* Washington, DC: U.S. Department of Education, National Center for Education Statistics (NCES 2007-468).

Hair, Jr., J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). *Multivariate data analysis* (6th ed.). Upper Saddle River, NJ: Pearson Education, Inc.

Halpin, G., & Halpin, G. (1996). *College freshman survey: Engineering Form.* Auburn University, AL: Auburn University.

Harackiewicz, J. M., Barron, K. E., Tauer, J. M., & Elliott, A. J. (2002). Predicting success in college: A longitudinal study of achievement goals and ability measures as predictors of interest and performance from freshman year through graduation. *Journal of Educational Psychology, 94*, 562-575.

Hawkins, E. F., Stancavage, F. B., & Dossey, J. A. (1998). *School policies and practices affecting instruction in mathematics: Findings from the national assessment of educational progress.* Washington, DC: U.S. Department of Education, Office of Educational Research and Improvement (NCES 1998-495).

Heinze, L. R., Gregory, J. M., & Rivera, J. (2003). *Math readiness: The implications for engineering majors*. Paper presented at the Frontiers In Engineering Conference, Boulder, CO.

Henson, K. T. (2001). *Curriculum planning: Integrating multiculturalism, constructivism, and education reform* (2nd ed.). Long Grove, IL: Waveland Press.

Horizon Research, Inc. (2000). *Inside the classroom: Observation and analytic protocol*. Chapel Hill, NC: Horizon Research, Inc.

Horizon Research, Inc. (2006). *Local systemic change: Principal questionnaire*. Chapel Hill, NC: Horizon Research, Inc.

House, J. D. (1993). Achievement-related expectancies, academic self-concept, and mathematics performance of academically underprepared adolescent students. *The Journal of Genetic Psychology, 154*, 61-71.

House, J. D. (1995a). Noncognitive predictors of achievement in introductory college chemistry. *Research in Higher Education, 36*, 473-490.

House, J. D. (1995b). Noncognitive predictors of achievement in introductory college mathematics. *Journal of College Student Development, 36*, 171-181.

House, J. D. (1995c). The predictive relationship between academic self-concept, achievement expectancies, and grade performance in college calculus: Replications and refinements. *The Journal of Social Psychology, 135*, 111-112.

House, J. D. (2000). Academic background and self-beliefs as predictors of student grade performance in science, engineering, and mathematics. *International Journal of Instructional Media, 27*, 207-220.

House, J. D., Keely, E. L., & Hurst, R. S. (1996). Relationship between learner attitudes, prior achievement, and performance in a general education course: A multiinstitutional study. *International Journal of Instructional Medial, 23*, 257-271.

Jones, P. S., & Coxford, Jr., A. F. (1970). Part one: Mathematics in the evolving schools. In National Council of Teachers of Mathematics, *A history of mathematics education in the United States and Canada: Thirty-second yearbook.* Washington DC: National Council of Teachers of Mathematics.

Kaestle, C. E. (1983). *Pillars of the republic: Common schools and American society, 1780-1860*. New York: Hill and Wang.

Kimmel, H., & Rockland, R. (2002). *Incorporation of pre-engineering lessons into secondary science classrooms.* Paper presented at the Frontiers In Engineering Conference, Boston, MA.

Klein, D. (2003). A brief history of American K-12 mathematics education in the 20th century. In J. M. Royer (Ed.), *Mathematical cognition* (pp. 175-259). Greenwich, CT: Information Age Publishing.

Klingbeil, N. W., Mercer, R.E., Rattan, K. S., Raymer, M. L., & Reynolds, D. B. (2005). *The WSU model for engineering mathematics education*. Paper presented at the ASEE Annual Conference, Portland, OR.

Klingner, J. K., Ahwee, S., Pilonieta, P., & Menendez, R. (2003). Barriers and facilitators in scaling up research-based practices. *Exceptional Children, 69*, 411-429.

Kuncel, N. R., Credé, M., & Thomas, L. L. (2005). The validity of self-reported grade point averages, class ranks, and test scores: A meta-analysis and review of the literature. *Review of Educational Research, 75*, 63-82.

Lackey, L. W., Lackey, W. J., Grady, H. M., & Davis, M. T. (2003). Efficacy of using a single, non-technical variable to predict the academic success of freshmen engineering students. *Journal of Engineering Education, 92*, 41-48.

LeBold, W. K., & Ward, S. K. (1988). *Engineering retention: National and institutional perspectives*. Paper presented at the ASEE Annual Conference, Portland, OR.

Lei, P., & Wu, Q. (2007). An NCME instructional module on introduction to structural equation modeling: Issues and practical considerations. *Educational Measurement: Issues and Practice, 26*, 33-43.

Litz, C. E. (1975). *Horace Mann and the sectarian controversy*. *Education, 95*, 280-286.

Litzinger, T. A., Wise, J. C., & Lee, S. H. (2005). Self-directed learning readiness among engineering undergraduate students. *Journal of Engineering Education, 94*, 215-221.

Lunenberg, F. C., & Ornstein, A. C. (2004). *Educational administration: Concepts and practices* (4th ed.). Belmont, CA: Wadsworth/Thomson Learning.

Mann, W. R. (1976). Some disquieting effects of calculus in high school. *The High School Journal, 59*, 237-239.

Mayer, R. E. (2003).Mathematical problem solving. In J. M. Royer (Ed.), *Mathematical cognition* (pp. 69-92). Greenwich, CT: Information Age Publishing.

Meyers, L. S., Gamst, G., & Guarino, A. J. (2006). *Applied multivariate research: Design and interpretation*. Thousand Oaks, CA: Sage Publications.

Mitchell, J. H., Hawkins, E. F., Jakwerth, P. M., Stancavage, F. B., & Dossey, J. A. (1999). *Student work and teacher practices in mathematics*. Washington, DC: U.S. Department of Education, Office of Educational Research and Improvement (NCES 1999-453).

Mitchell, J. H., Hawkins, E. F., Stancavage, F. B., & Dossey, J. A. (1999). *Estimation skills, mathematics-in-context, and advanced skills in mathematics: Results from three studies of the national assessment of educational progress 1996* *mathematics assessment.* Washington, DC: U.S. Department of Education, Office of Educational Research and Improvement (NCES 2000-451).

Moller-Wong, C., & Eide, A. (1997). An engineering student retention study. *Journal of Engineering Education, 86*, 7-15.

Murtaugh, P. A., Burns, L. D., & Schuster, J. (1999). Predicting the retention of university students. *Research in Higher Education, 40*, 355-371.

National Academy of Engineering. (2005). *Educating the engineer of 2020: Adapting engineering education to the new century*. Washington DC: National Academies Press.

National Commission on Excellence in Education. (1983) *A nation at risk*. Washington, DC: U.S. Department of Education. Retrieved April 26, 2007 from http://www.ed.gov/pubs/NatAtRisk/intro.html.

National Committee on Mathematical Requirements. (1923). The reorganization of mathematics in secondary education. Mathematical Association of America. In J. K. Bidwell, & R. G. Clason (Eds.) (1970), *Readings in the history of mathematics education*. Washington, DC: National Council of Teachers of Mathematics.

National Council of Teachers of Mathematics. (2000). *Principles and standards for school mathematics*. Reston, VA: National Council of Teachers of Mathematics.

National Science Board. (2004). *Science and engineering education indicators 2004.* Arlington, VA: National Science Foundation.

National Science Board. (2006a). *America's pressing challenge – Building a stronger foundation: A companion to science and engineering indicators 2006*. Arlington, VA: National Science Foundation.

National Science Board. (2006b). *Science and engineering education indicators 2006.* Arlington, VA: National Science Foundation.

Nixon, C. T., & Frost, A. G. (1990). The study habits and attitudes inventory and its implications for students' success. *Psychological Reports, 66*, 1075-1085.

No Child Left Behind Act, 20 U.S.C. § 6301 et seq. (2001). Retrieved January 20, 2005 from http://www.ed.gov/policy/elsec/leg/esea02/index.html.

Noble, J. P., Roberts, W. L., & Sawyer, R. L. (2006). *Student achievement, behavior, perceptions, and other factors affecting ACT scores*. Iowa City, IA: ACT, Inc. (ACT Research Report Series 2006-1).

Pedhazur, E. J. (1997). *Multiple regression in behavioral research: Explanation and prediction* (3rd ed.). Samford, CT: Thomson Learning, Inc.

Perie, M., Moran, R., Lutkus, A. D., & Tirre, W. (2005). *NAEP 2004 trends in academic progress: Three decades of student performance in reading and mathematics.* Washington, DC: U.S. Department of Education, Institute of Education Science, National Center for Education Statistics (NCES 2005-464).

Peterson, N. S., Kolen, M. J., & Hoover, H. D. (1989). Scaling, norming, and equating. In R. L. Linn (Ed.), *Educational measurement* (3rd ed.) (pp. 221-262). New York: Macmillan Publishing Company.

Rigby, K., & Harrell, D. (2005). *Issues in developing a high school pre-engineering program*. Paper presented at the Frontiers In Engineering Conference, Indianapolis, IN.

Sadler, P. M., & Tai, R. H. (2001). Success in introductory college physics: The role of high school preparation. *Science Education, 85*, 111-136.

Saylor, J. G., Alexander, W. M., & Lewis, A. J. (1981). *Curriculum planning for better teaching and learning* (4th ed.). New York: Holt, Rinehart, and Winston.

Schwartz, S., Regan, T., & Marshall, D. (1997). *A pre-engineering high school course in engineering design*. Paper presented at the Frontiers in Engineering Conference, Pittsburgh, PA.

Shaughnessy, M. F., Spray, K., Moore, J., & Siegel, C. (1995). Prediction of success in college calculus: Personality, scholastic aptitude test, and screening scores. *Psychological Reports, 77*, 1360-1362.

Shettle, C., Roey, S., Mordca, J., Perkins, R., Nord, C., Teodorovic, J., Brown, J., Lyons, M., Averett, C., & Kastberg, D. (2007). *The nation's report card: America's high school graduates.* Washington, DC: U.S. Department of Education, National Center for Education Statistics (NCES 2007-467).

Shuman, L., Besterfield-Sacre, M., Budny, D., Larpkiattaworn, S., Muogboh, O., Provezis, S., & Wolfe, H. (2003). *What do we know about our entering students and how does it impact upon performance?* Paper presented at the ASEE Annual Conference, Nashville, TN.

Smith, R. M., & Schumacher, P. A. (2005). Predicting success for actuarial students in undergraduate mathematics courses. *College Student Journal, 39*, 165-177.

Spring, J. (2005). *The American school: 1642-2004*. New York: McGraw-Hill.

Thorndike, R. L. (1951). Reliability. In E. F. Linquist (Ed.), *Educational measurement*. Washington, DC: American Council on Education.

TIMSS Study Center. (1998). *Mathematics teacher questionnaire: Main survey*. Chestnut Hill, MA: Boston College.

van Alphen, D. K., & Katz, S. (2001). A study of predictive factors for success in electrical engineering. Paper presented at the ASEE Annual Conference, Albuquerque, NM.

Wesley, J. C. (1994). Effects of ability, high school, achievement, and procrastinatory behavior on college performance. *Educational and Psychological Measurement, 54*, 404-408.

Westat. (2000). *National Survey of Science and Mathematics Education*. Rockville, MD: Westat.

Wilhite, P., Windham, B., & Munday, R. (1998). Predictive effects of high school calculus and other variables on achievement in a first-semester college calculus course. *College Student Journal, 32*, 610-615.

Wise, J., Lee, S. H., Litzinger, T. A., Marra, R. M., & Palmer, B. (2001). *Measuring cognitive growth in engineering undergraduates: A longitudinal study*. Paper presented at the ASEE Annual Conference, Albuquerque, NM.

Wulf, W. A., & Fisher, G. M. C. (2002). A makeover for engineering education. *Issues in Science and Technology, 18*(3). Retrieved May 7, 2007 from http://www.issues.org/18.3/p_wulf.html.

Zhang, G., Anderson, T. J., Ohland, M. W., & Thorndyke, B. R. (2004). Identifying factors influencing engineering student graduation: A longitudinal and cross-institutional study. *Journal of Engineering Education, 93*, 313-320.

APPENDICES

APPENDIX A

INSTITUTIONAL REVIEW BOARD

AUBURN

UNIVERSITY

Office of Human Subjects Research
307 Samford Hall
Auburn University, AL 36849

Telephone: 334 844 5966
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August 2, 2007

MEMORANDUM TO:	Jennifer Bell Education Foundations Leadership and Technology
PROTOCOL TITLE:	"Cognitive and Non-cognitive Factors Related to Academic Success in Quantitative Pre-engineering Courses"
IRB FILE NO.:	07-165 EX 0707
APPROVAL DATE: EXPIRATION DATE:	July 31, 2007 July 30, 2008

The referenced protocol was approved "Exempt" from further review under by IRB procedure on July 31, 2007 under 45 CFR 46.101 (b)(2):

> "Research involving the use of educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures or observation of public behavior unless:
> (i) information obtained is recorded in such a manner that human subjects can be identified, directly or through identifiers linked to the subjects; and
> (ii) any disclosure of the human subjects' responses outside the research could reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, or reputation."

You should retain this letter in your files, along with a copy of the revised protocol and other pertinent information concerning your study. If you should anticipate a change in any of the procedures authorized in this protocol, you must request and receive IRB approval prior to implementation of any revision. Please reference the above IRB file number in any correspondence regarding this project.

If you will be unable to file a Final Report on your project before July 30, 2008, you must submit a request for an extension of approval to the IRB no later than July 16, 2008. If your IRB authorization expires and/or you have not received written notice that a request for an extension has been approved prior to July 30, 2008, you must suspend the project immediately and contact the Office of Human Subjects Research for assistance.

A Final Report will be required to close your IRB project file.

If you have any questions concerning this Board action, please contact the Office of Human Subjects Research at 844-5966.

Sincerely,

Niki L. Johnson, JD, MBA, Director
Office of Human Subjects Research
Research Compliance Auburn University

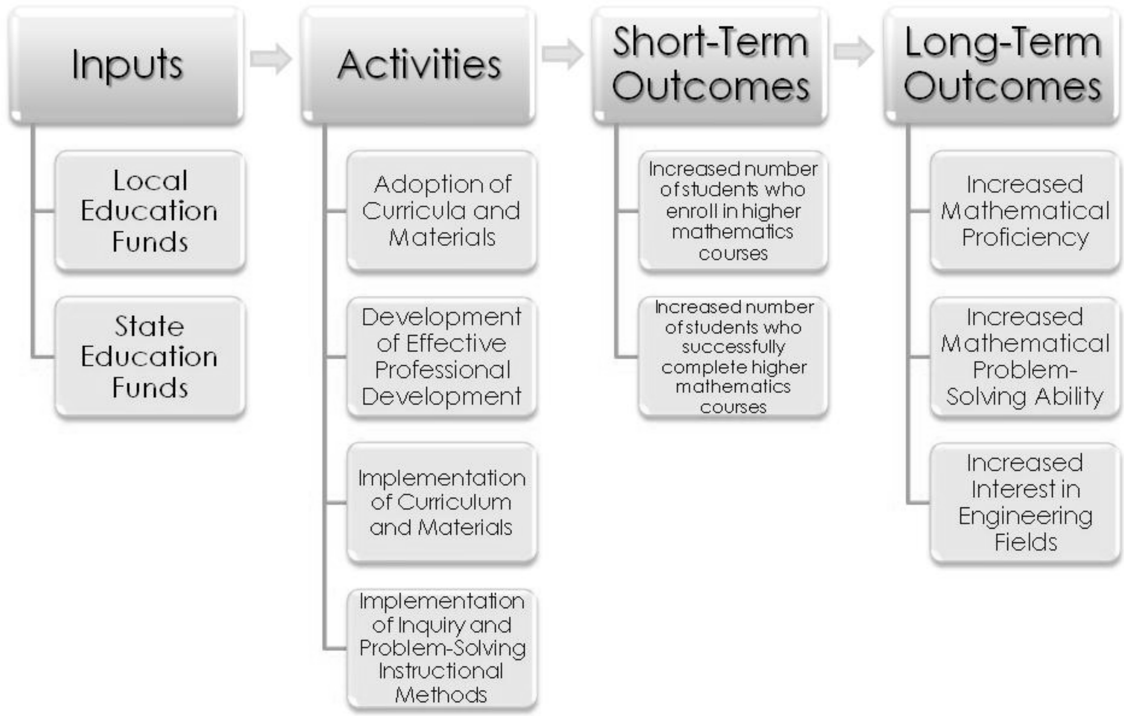
Enclosure

cc: Dr. Jose Llanes
Dr. Glennelle Halpin

APPENDIX B

LOGIC MODEL

Logic Model


Inputs
Local Education Funds
State Education Funds
Activities
Adoption of Curricula and Materials
Development of Effective Professional Development
Implementation of Curriculum and Materials
Implementation of Inquiry and Problem-Solving Instructional Methods
Short-Term Outcomes
Increased number of students who enroll in higher mathematics courses
Increased number of students who successfully complete higher mathematics courses
Long-Term Outcomes
Increased Mathematical Proficiency
Increased Mathematical Problem-Solving Ability
Increased Interest in Engineering Fields

APPENDIX C

GEOMETRY CURRICULUM UNITS

Unit: Land and Water Navigation **Subject**: Geometry **Grade Level**: 9

NCTM Standards-based Expectations:

IC1; IC2; IIA1; IIB1; IIB4; IIIA1; IIIA3; IIIB1; IIIB2; IIID1; IIID4; IIID5; VB3; VB5; VC1; VC2; VC3.

Engineering Connection:

- General Engineering
- Naval Architecture & Marine Engineering

Mathematical Concepts:

- Coordinate planes
- Total, average, and maximum distances in one and two dimensions
- Isosceles and equilateral triangles
- 30° - 60° right triangle relationships
- Pythagorean theorem
- Parallel lines, transversals, and corresponding angles
- Scaling

Learning Opportunities:

During this unit, all students will:

- Apply the concepts of coordinates and cardinal directions to navigation.
- Apply the concept of dead reckoning to navigation.
- Contrast relative and absolute locations.
- Explain how to use a map and compass to triangulate two known locations in order to find an unknown location.

- Identify the similarities and differences between navigation on water and land.
- Read, explain, and use compass directions to determine a location on land maps and nautical charts.
- Use velocity and time to determine location.
- Utilize the formula for distance (distance equals speed multiplied by time).

Key Terms:

- Dead reckoning
- GPS
- Latitude
- Longitude
- Line of position
- Triangulation
- Vectors

Equipment:

- Compass
- GPS
- Land maps
- Nautical charts
- Nautical slide ruler
- Scientific calculator

Performance Assessment:

Develop a grid chart. Chart a course. At 10-minute intervals, provide cardinal directions, latitudinal and longitudinal directions, speed, and distance. Based on your plotted course, use vectors to determine total distance traveled.

Unit: Horticulture: Landscape Design **Subject**: Geometry **Grade Level**: 9

NCTM Standards-based Expectations:

IB1; IC2; IIA1; IIB2; IIB4; IIIA1; IIIA3; IIIB1; IIIB2; IIID1; IIID4; IIID5; VB1; VB3; VB4; VC3.

Engineering Connection:

- Agricultural Engineering
- Environmental Engineering
- Geological Engineering

Mathematical Concepts:

Circles

- Area
- Circumference
- Chords

Learning Opportunities:

During this unit, all students will:

- Describe the specific relationships and properties of arcs and angles that are part of a circle.
- Detail the rationale for plant selections and other landscaping decisions.
- Explain that lines and secants, which are part of a circle, have relationships and properties and how to use these relationships and properties to determine the length of line segments and congruent segments.

Key Terms:

- Center
- Chord
- Circle
- Circumference
- Congruence
- Diameter
- Major arcs
- Minor arcs
- Radius
- Secant
- Tangent

Equipment:

- Scientific calculator

Performance Assessment:

Given a parcel of land with an area of 4,800 square feet, design a landscape. Include rationale for selection of shapes, turfs, plants, and other structures. Projected budget and scale drawing should also be included.

Unit: Bridge Building **Subject**: Geometry **Grade Level**: 9

NCTM Standards-based Expectations:

IA1; IB1; IC2; IIA1; IIB1; IIB2; IIB4; IIIA1; IIIB1; IIIB2; IIID1; IIID2; IIID4; IIID5; IVB4; VA3; VA6; VB3; VB5; VC3; VD1.

Engineering Connection:

Civil Engineering

Mathematical Concepts:

Three-dimensional shapes

- Spheres
- Cylinders
- Cones
- Cubes
- Pyramids

Learning Opportunities:

During this unit, all students will:

- Apply the concept of structural design and testing.
- Determine efficiency rating and critical load.
- Explain the impact of construction materials on critical load.

Key Terms:

- Critical load
- Edge
- Efficiency rating
- Face
- Vertex

Equipment:

- Scientific calculator

Performance Assessment:

Design a two-dimensional sketch for a bridge. Denote the intended purpose, construction materials, and dimensions. Construct a three-dimensional model to scale from the sketch. Determine efficiency rating and critical load for your structure.

Unit: Adaptive Devices **Subject**: Geometry **Grade Level**: 9

NCTM Standards-based Expectations:

IA1; IB1; IC2; IIA1; IIB1; IIB2; IIB4; IIIA1; IIIB1; IIIB2; IIIC1; IIIC2; IIID1; IIID2; IIID4; IIID5; IVB4; VA6; VB3; VB5; VC3; VD1.

Engineering Connection:

- Bioengineering
- Industrial Engineering
- Manufacturing Engineering
- Mechanical Engineering

Mathematical Concepts:

- Symmetry
- Transformations

Learning Opportunities:

During this unit, all students will:

- Describe the symmetry of geometric figures with respect to point, line, and plane.
- Explain the difference between adaptive and assistive devices.

Key Terms:

- Dilation
- Enlargement
- Isometry
- Projection
- Reduction
- Reflection
- Rotation
- Translation

Equipment:

- Scientific calculator

Performance Assessment:

Explain a situation that could benefit from an adaptive or assistive device. Develop a device or improve an existing device for this situation. Include a drawing, model, materials list, and estimated costs of production.

Unit: Simple and Complex Machines **Subject**: Geometry **Grade Level**: 9

NCTM Standards-based Expectations:

IA1; IB1; IC2; IIA1; IIB1; IIB4; IIIA1; IIIB1; IIIB2; IIID1; IIID2; IIID3; IIID4; IIID5; IVB4; VA3; VA6; VB3; VB5; VC3; VD1.

Engineering Connection:

- Industrial Engineering
- Manufacturing Engineering
- Mechanical Engineering

Mathematical Concepts:

- Euclid's axioms
- Euclid's postulates

Learning Opportunities:

During this unit, all students will:

- Identify the types of simple machines and their uses.
- Explain how force and distance impact the amount of work.
- Explain how simple machines reduce the amount of work.
- Compare and contrast simple and complex machines.

Key Terms:

- Distance
- Force
- Inclined plane (wedge, screw)
- Lever (first class, second class, third class)
- Line
- Plane
- Point

- Pulley
- Surface
- Wheel and axle
- Work

Equipment:

- Scientific calculator

Performance Assessment:

Describe a problem that could benefit from a simple machine. Design and construct a simple or complex machine to resolve the problem. Include the calculations, diagrams, and rationale.

Unit: Friction **Subject**: Geometry **Grade Level**: 9

NCTM Standards-based Expectations:

IB1; IC2; IIB2; IIB4; IIIA1; IIID4; IIID5; VA6; VB3; VB5; VC3.

Engineering Connection:

- Architectural Engineering
- Construction Engineering
- Civil Engineering

Mathematical Concepts:

- Surface area

Learning Opportunities:

During this unit, all students will:

- Identify occurrences of friction in real world settings.
- Explain the difference between static and kinetic friction.
- Describe how weight affects friction.
- Identify methods for reduction in friction.

Key Terms:

- Coefficient of friction
- Friction (static and kinetic)

Equipment:

- Scientific calculator

Performance Assessment:

Develop a product that could be affected by friction. Provide a scale diagram to illustrate your product's modifications to decrease/increase friction.

APPENDIX D

ALGEBRA II CURRICULUM UNITS

Unit: Thermodynamics **Subject**: Algebra II **Grade Level**: 10

NCTM Standards-based Expectations:

IB1; IC2; VA1; VA2; VA4; VA6; VB1; VB2; VB3; VB5; VC2; VC3.

Engineering Connection:

- Chemical Engineering
- Electrical Engineering

Mathematical Concepts:

- Addition of functions
- Absolute-rate equations
- Inequalities
- Transformation of functions

Learning Opportunities:

During this unit, all students will:

- Describe the types of functions: linear, absolute value, greatest integer, inverse variation, quadratic, cubic, exponential, logarithmic, and trigonometric.
- Compare and contrast even and odd functions.
- Explain the similarities between solving equalities and inequalities.
- Describe and illustrate thermodynamic states and processes.
- Explain the first and second law of thermodynamics.

Key Terms:

- Property of addition
- Property of subtraction
- Property of multiplication
- Property of division.

Equipment:

- Scientific/graphing calculator

Performance Assessment:

Design three cylindrical metal conductors. Include scale drawing, dimensions, cross-sectional area, and materials of construction. The cylinder will be arranged from left to right between a HTR and LTR. Calculate the temperatures of the two interfaces and the rate at which heat is conducted into the LTR.

Unit: Viral Diseases **Subject**: Algebra II **Grade Level**: 10

NCTM Standards-based Expectations:

IA1; IB1; IC2; IIB2; IIIC2; IVA2; IVA4; IVB1; IVB2; IVB3; IVB4; IVB5; IVD1; IVD2; IVD3; IVD4; IVD5; VA3; VA4; VA6; VB2; VB3; VB5; VC3; VD1.

Engineering Connection:

Biomedical Engineering

Mathematical Concepts:

- Linear functions and models
- Systems of equations
- Probability distributions
- Tree diagrams

Learning Opportunities:

During this unit, all students will:

- Describe a viral disease and how it replicates itself.
- Explain how the immune system responds to viral diseases.
- Illustrate the four methods of solving systems of equations: graphing, substitute, addition-subtraction, and multiplication with addition-subtraction.
- Illustrate the four ways of graphing linear equations: plotting points, using intercepts, and using slope-intercept formula.
- Use the standard form of a linear equation.

Key Terms:

- Epidemiology
- Host
- Virus

Equipment:

- Scientific/graphing calculator

Performance Assessment:

Track a virus (actual or hypothetical). Develop a plan for decreasing the spread of the viral disease. Include target population and detailed action plan.

Unit: HVAC Systems **Subject**: Algebra II **Grade Level**: 10

NCTM Standards-based Expectations:

IC2; IIA1; IIB1; IIB2; IIB4; IIIA1; IIIC1; IIIC2; IIID1; IIID4; IIID5; VA1; VA2; VA4; VA6; VB3; VB5; VC3.

Engineering Connection:

- Architectural Engineering
- Civil Engineering
- Construction Engineering
- Mechanical Engineering

Mathematical Concepts:

- Voronoi diagram
- Area
- Volume
- Weighted averages
- Algorithm
- Polygons
- Heron's formula
- Pick's formula
- Reflection
- Iteration

Learning Opportunities:

During this unit, all students will:

- Describe the process for determining volume and area of geometric figures.
- Explain the interrelationship between heating, ventilating, and air-conditioning.

Key Terms:

- Air quality
- Ductwork
- Heat transfer
- Room air distribution
- Thermodynamics

Equipment:

- Scientific/graphing calculator

Performance Assessment:

Design a structure. Include a drawing to scale with a heating and air conditioning diagram based on the square footage.

Unit: Cellular Respiration **Subject**: Algebra II **Grade Level**: 10

NCTM Standards-based Expectations:

IA1; IA2; IC2; IIB1; IIB4; IVA1; IVA2; IVA3; IVA4; IVA5; IVB1; IVB2; VA1; VA3; VA5; VA6; VB1; VB3; VB4; VB5; VC2; VC3; VD1.

Engineering Connection:

- Biological Engineering
- Biomedical Engineering
- Chemical Engineering
- Environmental Engineering

Mathematical Concepts:

- Additive growth
- Multiplicative growth
- Linear equations
- Exponential equations
- Recursive equations
- Rate of growth
- Time-series graphs
- Web diagrams
- Properties of exponents
- Quadratic functions

Learning Opportunities:

During this unit, all students will:

- Explain the effect of environmental factors on cellular respiration.
- Explain the methods for solving a quadratic function: factoring, using the square-root property, completing the square, and using the quadratic formula.
- Graph a parabola when given a quadratic function.
- Identify the vertex, axis of symmetry, x-intercept, and y-intercept when given a quadratic function.

Key Terms:

- Cellular respiration
- Environmental factors
- Fermentation
- Population growth

Equipment:

- Scientific/graphing calculator

Performance Assessment:

Design an experiment to test cellular respiration based on real-world application. Decide whether to control for environmental factors during the experiment. Use the scientific method to conduct the experiment. Include observational data, data analysis, and conclusions.

Unit: Pipeline Design **Subject**: Algebra II **Grade Level**: 10

NCTM Standards-based Expectations:

IC2; IIA1; IIB1; IIIC1; IIIC2; IVA3; IVA4; IVB1; IVB2; IVB3; IVB4; IVB5; VA3; VA6; VB1; VB3; VB4; VB5; VC2; VC3; VD1.

Engineering Connection:

- Civil Engineering
- Industrial Engineering
- Manufacturing Engineering

Mathematical Concepts:

- Rate of change
- Slope
- Piecewise equations
- Linear transformations
- Symmetric difference quotient
- Parametric equations

Learning Opportunities:

During this unit, all students will:

- Describe the environmental influences on the motion of an object.
- Determine slope when given two sets of coordinates.
- Explain that parallel lines have the same slope and perpendicular lines have negative reciprocal slopes.

Key Terms:

- Force
- Motion
- Position

Equipment:

- Scientific/graphing calculator

Performance Assessment:

Given a specific terrain, design a pipeline to transport a golf ball. Include a scale drawing, calculations for intended transported material, estimated construction costs, and three-dimensional model. Develop an evaluation plan to test and assess your pipeline.

APPENDIX E

PRE-CALCULUS/TRIGONOMETRY UNITS

Unit: Business Plan **Subject**: Pre-Calculus/Trigonometry **Grade Level**: 11

NCTM Standards-based Expectations:

IA1; IB1; IC2; IIB1; IIIC2; IIID4; IIID5; IVB4; IVB5; IVD1; IVD2; VA3; VA4; VA5; VA6; VB3; VB5; VC3; VD1.

Engineering Connection:

Engineering Management

Mathematical Concepts:

Exponential and logarithmic functions

- Exponential functions
- Base *e*
- Logarithmic scale
- Graphs of logarithmic functions
- Logarithms and bases
- Changing bases
- Logarithmic functions
- Composition and inverse functions

Learning Opportunities:

During this unit, all students will:

- Describe a market analysis using logarithmic functions.

Key Terms:

- Mission
- Products
- Services
- Strategy

Equipment:

- Graphing calculator

Performance Assessment:

You have decided to open your own business. The bank will finance you business, but they want the following items before approving the loan:

1. Business plan, including name of the proposed business, location, product or service, and target customers)
2. Marketing plan, including an advertisement with the business's logo and slogan
3. Budget, including the initial loan amount and expenses
4. Projected growth, including graphics, variables, and calculations

Unit: Electrical Circuits **Subject**: Pre-Calculus/Trigonometry **Grade Level**: 11

NCTM Standards-based Expectations:

IA2; IB1; IC2; IIA1; IIID5; VA5; VA6; VB3; VB5; VC3.

Engineering Connection:

Electrical Engineering

Mathematical Concepts:

Polynomials

- One-term polynomials
- Polynomials with more than one term
- Cubic equations
- Complex numbers
- Fundamental theorem of algebra
- Rational functions
- Power series

Learning Opportunities:

During this unit, all students will:

- Distinguish between series and parallel circuits and their effect on current flow.
- Explain the properties of complex numbers: closure, commutative, associative, identity, distributive, additive, inverse, and multiplicative inverse.

Key Terms:

- Active clamping circuit
- Active clipping circuit
- Current flow
- Parallel circuit
- Passive clamping circuit
- Passive clipping circuit
- Resistance
- Series circuit

Equipment:

- Graphing calculator

Performance Assessment:

Develop a series or parallel circuit. Based on your design, graph the electrical input and output. Include a scale drawing of the circuit and computations for your graphed electrical input and output.

Unit: Wave Motion **Subject**: Pre-Calculus/Trigonometry **Grade Level**: 11

NCTM Standards-based Expectations:

IIIA1; IIIA2; IIIA3; IIIA4; IIIB1; IIIB2; IIID1; IIID4; IIID5; VA2; VA3; VA4; VA5; VA6; VB3; VB4; VB5; VC3.

Engineering Connection:

- Aerospace Engineering
- Ocean Engineering

Mathematical Concepts:

Trigonometric functions

- Periodic functions
- Periods and amplitude
- Sine function
- Cosine function
- Tangent function
- Radians and degrees
- Inverse trigonometric functions

Learning Opportunities:

During this unit, all students will:

- Distinguish between the three trigonometric functions and their inverses.
- Display a sine, cosine, and tangent function graph.

Key Terms:

- Amplitude
- Crest
- Period
- Trough
- Wavelength

Equipment:

- Computer/internet access
- Graphing calculator

Performance Assessment:

Design a musical instrument. Graph the sound waves from the instrument using FlexiMusic software (www.fleximusic.com). Using the graph, provide calculations and diagrams of the sound waves.

Unit: Aeronautical Navigation **Subject**: Pre-Calculus/Trigonometry **Grade Level**: 11

NCTM Standards-based Expectations:

IA3; IB2; IC1; IIA1; IIIA1; IIIA2; IIIA3; IIIA4; IIIB1; IIIB2; IIID2; IIID4; IIID5; VA6; VB3; VB4; VB5; VC3.

Engineering Connection:

Aerospace Engineering

Mathematical Concepts:

Coordinate systems and vectors

- Polar coordinates
- De Moivre's theorem
- Vectors
- Vector and parametric equations in two dimensions
- Vector equations in three dimensions
- Matrices

Learning Opportunities:

During this unit, all students will:

- Be able to convert rectangular coordinates to polar coordinates.
- Identify the similarities and differences between navigation on air, water, and on land.
- Read, explain, and use compass directions to determine a location on aeronautical charts.

Key Terms:

- GPS
- Latitude
- Longitude
- Line of position
- Triangulation
- Vectors

Equipment:

- Graphing calculator

Performance Assessment:

Design a transportation vehicle. Include scale drawing, estimated construction costs, computations, and actual prototype of the vehicle. The aerodynamics will be assessed using a wind tunnel.

Unit: Optics **Subject**: Pre-Calculus/Trigonometry **Grade Level**: 11

NCTM Standards-based Expectations:

IB1; IC2; IIIA1; IIIA4; IIIB1; IIIB2; IIIC1; IIIC2; IIID1; IIID4; IIID5; VA6; VB3; VB5; VC3.

Engineering Connection:

- Aerospace Engineering
- Mechanical Engineering

Mathematical Concepts:

Analytic geometry

- Circles
- Parabolas
- Ellipse
- Hyperbola
- Reflection property

Learning Opportunities:

During this unit, all students will:

- Illustrate Fermat's principle (law of reflection).
- Distinguish between plane and spherical mirrors.
- Discriminate the terms of reflection and refraction.
- Describe how lenses and magnifying instruments transform light rays.

Key Terms:

- Concave
- Convex
- Diffuse surface
- Geometric optics
- Light rays
- Mirror
- Optical axis
- Specular surface

Equipment:

- Graphing calculator

Performance Assessment:

Design a spherical mirror (concave or convex). Use the law of reflection to calculate the geometric relationships with the optical axis and spherical mirror. Include a scale drawing with thickness and computations.

Unit: Introduction to Statistics **Subject**: Pre-Calculus/Trigonometry **Grade Level**: 11

NCTM Standards-based Expectations:

IA1; IB1; IB3; IC1; IC2; IIIB1; IIIB2; IIID1; IIID4; IIID5; IVA1; IVA2; IVA3; IVA4; IVA5; IVB1; IVB2; IVB3; IVB4; IVB5; IVC1; IVC2; IVC3; IVC4; IVD1; IVD2; IVD3; IVD4; VA1; VA2; VA3; VA6; VB1; VB2; VB3; VB4; VB5; VC2; VC3; VD1.

Engineering Connection:

General Engineering

Mathematical Concepts:

Counting and the binomial theorem

- Basic multiplication principle
- Addition principle
- Binomial theorem

Learning Opportunities:

During this unit, all students will:

- Explain the process of hypothesis testing
- Describe the strengths and limitations of different research designs
- Identify applications of a wide variety of statistical procedures
- Make accurate interpretations of statistical findings

Key Terms:

- Analysis of variance
- Frequency distribution
- General linear model
- Measures of central tendency
- Measures of variability
- Parameter

- Probability
- Regression
- Residuals
- Statistics
- Sampling
- Trend analysis

Equipment:

- Graphing calculator

Performance Assessment:

Create a dataset with at least three variables. Based on the measurement of the data, conduct a statistical analysis to determine statistical significance. The analysis results should include the formulas, calculations, and interpretations.

Unit: Dynamic Systems **Subject**: Pre-Calculus/Trigonometry **Grade Level**: 11

NCTM Standards-based Expectations:

IB1; IB3; IC1; IC2; IIB4; IVB4; IVB5; VA3; VB1; VB2; VB3; VB4; VB5; VC1; VC2; VC3; VD1.

Engineering Connection:

Civil Engineering

Mathematical Concepts:

Change with discrete dynamical systems

- Difference equations
- Constant change
- Linear change
- Proportional change
- Equilibrium values

Learning Opportunities:

During this unit, all students will:

- Distinguish between classic scientific approach and dynamic change approach.

Key Terms:

- Patterns of change

Equipment:

- Graphing calculator

Performance Assessment:

Based on a specific area of terrain, design a highway system. Include a description of the terrain including altitude and dimensions, topographical model, scale drawing, and estimated construction costs.

APPENDIX F

ADVANCED PLACEMENT CALCULUS AB CURRICULUM UNITS

Unit: Water Supply **Subject**: AP Calculus AB **Grade Level**: 12

NCTM Standards-based Expectations:

IB1; IB2; IB3; IIIA1; IIIA2; IIIA3; IIIA4; IIIB1; IIIB2; IIID4; IIID5; VA1; VA2; VA3; VA4; VA5; VB1; VB2; VB3; VB4; VB5; VC1; VC2; VC3; VD1.

Engineering Connection:

- Biosystems Engineering
- Civil Engineering
- Electrical Engineering
- Environmental Engineering

Mathematical Concepts:

Local linearity

- Graphs of basic families of functions
- Graphs of linear equations
- Graphs of algebraic simplifications

Learning Opportunities:

During this unit, all students will:

- Describe the basic families of functions.
- Determine whether an equation is linear or non-linear.

Key Terms:

- Function
- Linear equation
- Slope
- *y*-intercept

Equipment:

- Graphing calculator

Performance Assessment:

Consider a hypothetical city or town. Describe the population demographics and the municipality's location (i.e., geographic size and proximity to resources). Develop a water supply system for the hypothetical municipality. Include a scale drawing from the top and side views and estimated construction costs.

Unit: Market Growth **Subject**: AP Calculus AB **Grade Level**: 12

NCTM Standards-based Expectations

IA2; IA4; IB1; IB2; IB3; IIIA1; IIIA2; IIIA3; IIIA4; IIIB1; IIIB2; IIID4; IIID5; IVB1; IVB5; VA1; VA2; VA3; VA4; VA5; VB1; VB2; VB3; VB4; VB5; VC1; VC2; VC3; VD1.

Engineering Connection:

Chemical Engineering

Mathematical Concepts:

Functions and Limits

- Function notation, domain, and range
- Odd and even functions definitions and graphical properties
- Limit notation, including right- and left-hand limits
- Asymptotic behavior of rational and exponential functions using limit notation
- Estimating limits from graphs and from tables of values
- Calculating limits using algebra
- Presentation of a definition of a limit only to show students how a formal definition addresses the idea of "closeness" and how it excludes concern for what occurs when $x = a$
- Continuity and graphical properties of continuous functions, including Intermediate Value Theorem and Extreme Value Theorem.
- Investigating functions that are not continuous at x = a

Learning Opportunities:

During this unit, all students will:

- Utilize the Gompetz equation to fit data to growth curves.

Key Terms:

- Adaptation
- Asymptotes
- Continuity
- Deceleration
- Discontinuity
- Domain
- Fast-growth
- Limits
- Saturation

Equipment:

- Graphing calculator

Performance Assessment:

Develop a new product or technological innovation to be introduced in the market. Create data to illustrate its growth pattern. Use a simple exponential model of the form $1\text{-}e^{-x}$ and the Gompetz equation using the created data. Compare and contrast the two methods for graphing growth curves.

Unit: Amusement Park Design **Subject**: AP Calculus AB **Grade Level**: 12

NCTM Standards-based Expectations:

IA2, IA4, IB1, IB2, IB3, IIIA1, IIIA2, IIIA3, IIIB1, IIIB2, IIIB3, IIID1, IIID2, IIID3, IIID4, IIID5, IVB1, IVB2, IVB4, IVB5, VA1, VA2, VA3, VA4, VA5, VA6, VB1, VB2, VB3, VB4, VB5, VC1, VC2, VC3, VD1.

Engineering Connection:

- Aerospace Engineering
- Mechanical Engineering

Mathematical Concepts:

The derivative and applications of differentiation

- Definition of the derivative
- Instantaneous rate of change as the limiting value of average rate of change
- Investigating functions differentiable at $x = a$ as well as those not differentiable at $x = a$ algebraically and graphically
- The relationship between the graphs of f and f'
- Relative (local) extrema and the first derivative test
- Absolute extrema in the context of applied problems
- Derivatives of algebraic functions: power, sum, constant multiple, and product rules
- Derivatives of circular functions
- Composite functions
- Chain rule

- Implicit differentiation
- Related rates
- Second derivative: concavity and points of inflection
- Differential equations
- Relationship between differentiability and continuity
- Mean value theorem

Learning Opportunities:

During this unit, all students will:

- Use first and second derivatives to determine motion.
- Compare and contrast different guided motions along spatial curves.
- Graph a derivative function.

Key Terms:

- Derivatives
- Extrema

Equipment:

- Graphing calculator

Performance Assessment:

Design an amusement park ride. Include a scale drawing, estimated construction costs (labor and material), and three-dimensional model.

Unit: Rocket Design **Subject**: AP Calculus AB **Grade Level**: 12

NCTM Standards-based Expectations:

IA2, IA4, IB1, IB2, IB3, IIIA1, IIIA2, IIIA3, IIIB1, IIIB2, IIIB3, IIID1, IIID2, IIID3, IIID4, IIID5, IVB1, IVB2, IVB4, IVB5, VA1, VA2, VA3, VA4, VA5, VA6, VB1, VB2, VB3, VB4, VB5, VC1, VC2, VC3, VD1.

Engineering Connection:

- Aerospace Engineering
- Industrial Engineering

Mathematical Concepts:

The integral and applications of integration

- Riemann sums (left hand, right hand, and midpoint sums) to approximate the area of a region bounded by continuous functions
- Evaluating limits of Riemann sums over equal subdivisions to determine area of regions bounded by polynomial functions on the interval $[0, b]$
- Definite integral as a limit of Riemann sums
- The fundamental theorem of calculus
- Indefinite integrals: antiderivatives of known functions and using simple substitutions
- Integration by parts
- Numerical approximations to definite integrals using tables and graphs: Riemann sums and trapezoidal rule

- Using definite integrals whose integrands are velocity functions to show that accumulating rates of change in distance yields net distance traveled
- Rectilinear motion
- Volumes of known cross sections as limits of Riemann sums, including sums of discs, washers, cylindrical shells, and other cross-sectional slices.
- Average value of a function
- Variable separate differential equations involving simple polynomial and trigonometric functions

Learning Opportunities:

During this unit, all students will:

- Apply the average velocity method.
- Apply the trapezoidal rule.
- Apply polynomial interpolation.

Key Terms:

- Integral
- Velocity

Equipment:

- Graphing calculator

Performance Assessment:

Design a rocket. Include scale drawing, estimated construction costs, materials lists, and final product. Conduct 10 time trials and record the data. Determine the distance, s, covered by the rocket using the velocity data provided.

Unit: Loglinear Analysis **Subject**: AP Calculus AB **Grade Level**: 12

NCTM Standards-based Expectations:

IA2, IA4, IB1, IB2, IB3, IIIA1, IIIA2, IIIA3, IIIA4, IIIB1, IIIB2, IIIB3, IIID1, IIID2, IIID3, IIID4, IIID5, IVB1, IVB2, IVB4, IVB5, VA1, VA2, VA3, VA4, VA5, VA6, VB1, VB2, VB3, VB4, VB5, VC1, VC2, VC3, VD1.

Engineering Connection:

General Engineering

Mathematical Concepts:

Transcendental functions

- Definition of natural logarithm
- Properties of natural logarithms
- Logarithmic differentiation
- Inverse functions and their derivatives
- Exponential functions as inverses of logarithmic functions
- Definition of *e*
- Differentiation and integration involving e^u, a^u, and $\log_a u$
- Exponential growth and decay problems
- Inverse trigonometric functions and their derivatives

Learning Opportunities:

During this unit, all students will:

- State the properties of natural logarithms.
- Compare and contrast exponential functions and inverse trigonometric functions.

Key Terms:

- Categorical data
- *e*
- Natural logarithm
- Parameters

Equipment:

- Graphing calculator
- Statistical Package for Social Sciences (SPSS) software

Performance Assessment:

Design a longitudinal study. Include participants, data collection procedures, timeline, measures, and research question(s). Using SPSS software, enter mock data to illustrate your study. Conduct a loglinear analysis to answer your research questions.

APPENDIX G

LESSON PLAN DESIGN RATING SYSTEM

Lesson Plan Design Rating System

Title of Lesson Plan: ____

Subject: ___________________________ Grade Level: ________________

Directions: Using the following rating scale, rate each of these design elements as to the extent you observed them in this mathematics lesson.

Design	**1** Not at all	**2** Minimal	**3** Adequate	**4** Great Extent
a. The design of the lesson incorporated tasks, roles, and interactions consistent with investigative mathematics/science.	☐	☐	☐	☐
b. The instructional strategies and activities used in this lesson reflected attention to students' prior knowledge.	☐	☐	☐	☐
c. The instructional strategies and activities used in this lesson reflected attention to students' learning styles.	☐	☐	☐	☐
d. The resources available in this lesson contributed to its purpose.	☐	☐	☐	☐
e. The design of the lesson encouraged a collaborative approach to learning among the students.	☐	☐	☐	☐

Directions: Using the following rating scale, rate each of these content elements as to the extent you observed them in this mathematics lesson.

Content	**1** Not at all	**2** Minimal	**3** Adequate	**4** Great Extent
a. The mathematics content was appropriate for the developmental level of the intended students.	☐	☐	☐	☐
b. Mathematics was portrayed as a dynamic body of knowledge.	☐	☐	☐	☐
c. Appropriate connections were made to other areas of mathematics.	☐	☐	☐	☐
d. Appropriate connections were made to other disciplines.	☐	☐	☐	☐
e. The content had real-world applications.	☐	☐	☐	☐

Directions: Based on your review of this lesson, rate the design of this lesson.

1 The design did not reflect best practices in investigative mathematics.	**2**	**3**	**4**	**5** The design reflected best practices in investigative mathematics.
☐	☐	☐	☐	☐

Directions: Please respond to the following prompts in the space provided.

1. Give two suggestions for improving this lesson.

____

____

2. Provide any additional comments about this lesson.

____

____

APPENDIX H

SAMPLE MATHEMATICAL PROBLEM-SOLVING EXAMINATION AND SCORING RUBRIC

Sample Mathematical Problem-Solving Examination

Directions: Read each of the following prompts. Use your conceptual and procedural knowledge of mathematics to complete each task. Show all of your work for each step.

1. Your grandmother's birthday is next month. She would love to have a birdhouse as a birthday present.

   Tasks:
   1. Design a birdhouse using a scale drawing.
   2. Develop a materials list to build your design.
   3. Create a budget for all needed materials.

Sample Mathematical Problem-Solving Examination Scoring Rubric

Domain	**1**	**2**	**3**	**4**	**5**
Concepts	Inappropriate application of mathematical concepts was used.	Minimal evidence of concept application was shown.	Part of the response showed application of a mathematical concept.	Solid application of one mathematical concept was shown.	Integration of two or more mathematical concepts was used.
Procedures	Procedure was unclear or ineffective. Lacked use of appropriate procedures.	Procedure was under-developed.	Procedure was evident in partial. Rote skills or partial use of procedures.	Procedure was clear and evidence showed execution.	Procedure was complex, systematic, and supported. Full use of appropriate procedures.
Accuracy	Answer was correct.		Response contained errors/ mistakes.		Answer was incorrect.
Communication	Ineffective	Minimal	Partial development	Full development but contained unclear explanations.	Full development and clear explanations that used pictures, symbols, and/or vocabulary.

APPENDIX I

PROFESSIONAL DEVELOPMENT EXIT SURVEY

Professional Development Exit Survey

Subject(s) that you are teaching: ____

Date: ______________ Location: _________________________

Session: ____

Directions: Please rate the listed items using the rating scale.

	1 Unsatisfactory	2 Fair	3 Satisfactory	4 Excellent
a. Format of the session.	☐	☐	☐	☐
b. Content provided during the session.	☐	☐	☐	☐
c. Usefulness/Application of the activities to your classroom instruction.	☐	☐	☐	☐
d. Quality of lunch provided at the session.	☐	☐	☐	☐
e. Location (facilities) of the session.	☐	☐	☐	☐
f. Overall professional development experience.	☐	☐	☐	☐

Directions: Please respond to the following prompts in the space provided.

1. List two outstanding components of this session.

____

____

2. Give two suggestions for improving this session.

____

____

3. Provide any additional comments about this session.

____

____

Directions: Rate your level of need for the following professional development topics from 1, which indicates the most need, to 7, which indicates the least need.

______	Deepening my own content knowledge of mathematics.
______	Deepening my own content knowledge of performance standards.
______	Learning how to assess student learning.
______	Learning how to teach students with diverse learning needs.
______	Learning how to use inquiry/investigation-oriented teaching strategies.
______	Learning how to use technology in instruction.
______	Understanding student-thinking abilities.

Directions: Using the following rating scale, rate each of these skills regarding how important you feel they are for a student to be successful in mathematics.

	1 Not Important	**2** Somewhat Important	**3** Important	**4** Very Important
a. Remembering formulas and procedures.	☐	☐	☐	☐
b. Thinking in a sequential and procedural manner.	☐	☐	☐	☐
c. Understanding mathematical concepts, principles, and strategies.	☐	☐	☐	☐
d. Being able to think creatively.	☐	☐	☐	☐
e. Understanding how mathematics is used in the real world.	☐	☐	☐	☐
f. Being able to provide reasons to support their solutions.	☐	☐	☐	☐

Directions: Use the following rating scale to indicate the extent to which you are familiar with the *National Council of Teachers of Mathematics Standards.*

1 **Not at All**	**2** **Minimal**	**3** **Adequate**	**4** **Great Extent**
☐	☐	☐	☐

Directions: Read each of the following prompts and place a check mark beside the appropriate items to indicate your response. These prompts require more than one response; therefore, check all that apply.

1. During the last week, which of the following instructional activities have occurred with **your students**?

	Demonstration and guided practice sessions
☐	Listened and took notes during lecture presentation by teacher.
☐	Watched a demonstration.
☐	Worked in groups.
☐	Took field trips.
☐	Used mathematical problem-solving skills.
	Independent practice
☐	Answered textbook or worksheet questions.
☐	Made formal presentations to the rest of the class.
☐	Read from a textbook in class.
☐	Read other (non-textbook) subject-related materials in class.
☐	Recorded, represented, and/or analyzed data.
☐	Wrote reflections (e.g., in a journal).
	Lab activities
☐	Completed hands-on/laboratory activities or investigations.
☐	Designed or implemented independent investigation.
☐	Followed specific instructions in an activity or investigation.
☐	Participated in fieldwork.
☐	Prepared written lab reports.
☐	Worked on extended investigations or long-term projects (i.e., a week or more in duration).
	Assistive Technology
☐	Used computers as a tool (e.g., spreadsheets, data analysis).
☐	Used calculators or computers for learning or practicing skills.
☐	Used calculators or computers to develop conceptual understanding.
☐	Watched audiovisual presentations (e.g., videotapes, CD-ROMs, television, or films).

2. During the last week, which of the following student assessment activities have occurred in **your classroom**?

	<u>Summative</u>
☐	Gave predominantly short-answer tests (e.g., multiple-choice, true/false, fill in the blank).
☐	Gave tests requiring open-ended responses (e.g., descriptions, explanations).
☐	Graded student work on open-ended tasks using defined criteria (e.g., a scoring rubric).
☐	Reviewed student homework.
☐	Reviewed student portfolios.
	<u>Formative</u>
☐	Asked students questions during large group discussions.
☐	Conducted a pre-assessment to determine what students already know.
☐	Had students present their work to the class.
☐	Had students assess each other (peer evaluation).
☐	Observed students and asked questions as they worked individually.
☐	Observed students and asked questions as they worked in small groups.
☐	Reviewed student notebooks/journals.
☐	Used assessments embedded in class activities (e.g., informal assessments).

Thank you for your feedback.
Your opinion is taken into consideration
when planning future professional development sessions.

APPENDIX J

WEEKLY INFORMAL OBSERVATION FORM

Weekly Observational/Implementation Monitoring Checklist

Subject: ______________________________ Teacher: __________________________

Date: __________ Time: Start _____ End ______ Location: __________________

Lesson Topic/Objective(s): ____

Directions: Based on the time spent in the classroom and using the following continuum, describe the focus of this lesson:

1 Algorithms, Facts, and Vocabulary 100%	2 75/25	3 50/50	4 25/75	5 Mathematics/ Science Concepts 100%
☐	☐	☐	☐	☐

Directions: Using the following rating scale, rate each of these teacher/lesson indicators as to the extent you observed them during the mathematics lesson.

	1 Not at all	2 Minimal	3 Adequate	4 Great Extent
a. The instructional strategies were consistent with investigative mathematics/science.	☐	☐	☐	☐
b. The teacher appeared confident in his/her ability to teach mathematics.	☐	☐	☐	☐
c. The pace of the lesson was appropriate for the developmental level of the students.	☐	☐	☐	☐
d. The teacher's questioning strategies were likely to enhance the students' problem-solving ability.	☐	☐	☐	☐
e. Elements of abstract mathematics were included when appropriate.	☐	☐	☐	☐
f. Appropriate connections were made with real-world contexts.	☐	☐	☐	☐

Directions: Using the following rating scale, rate each of these student indicators as to the extent you observed them during the mathematics lesson.

	1 Not at all	2 Minimal	3 Adequate	4 Great Extent
a. Students were actively engaged with important ideas, which were relevant to the focus of the lesson.	☐	☐	☐	☐
b. Interactions between students reflected cooperative learning relationships.	☐	☐	☐	☐
c. The climate of the lesson encouraged students to generate ideas, hypothesis, and questions.	☐	☐	☐	☐

Directions: For each of the following behaviors, place a check mark beside the item if the behavior was included in the observed lesson.

	Demonstration and guided practice sessions
☐	Listened and took notes during lecture presentation by teacher.
☐	Made formal presentations to the rest of the class.
☐	Recorded, represented, and/or analyzed data.
☐	Used manipulatives.
☐	Watched a demonstration.
☐	Wrote reflections (e.g., in a journal).
	Lab activities
☐	Completed hands-on/laboratory activities or investigations.
☐	Designed or implemented independent investigation.
☐	Followed specific instructions in an activity or investigation.
☐	Prepared written lab reports.
	Assistive Technology
☐	Used computers as a tool (e.g., spreadsheets, data analysis).
☐	Used calculators or computers for learning or practicing skills.
☐	Used calculators or computers to develop conceptual understanding.
☐	Watched audiovisual presentations (e.g., videotapes, CD-ROMs, television, or films).

APPENDIX K

NCTM STANDARDS-BASED EXPECTATIONS

NCTM Expectations
(NCTM, 2000)

I. Number and Operations

A. Understand numbers, ways of representing numbers, relationships among numbers, and number systems.

In Grades 9 – 12, all students should:

- Develop a deeper understanding of very large and very small numbers and of various representations of them (IA1);
- Compare and contrast the properties of numbers and number systems, including the rational and real numbers, and understand complex numbers as solutions to quadratic equations that do not have real solutions (IA2);
- Understand vectors and matrices as systems that have some of the properties of the real-number system (IA3);
- Use number-theory arguments to justify relationships involving whole numbers (IA4).

B. Understand meanings of operations and how they relate to one another.

In Grades 9 – 12, all students should:

- Judge the effects of such operations as multiplication, division, and computing powers and roots on the magnitudes of quantities (IB1);
- Develop an understanding of properties of, and representations for, the addition and multiplication of vectors and matrices (IB2);
- Develop an understanding of permutations and combinations as counting techniques (IB3).

C. Compute fluently and make reasonable estimates.

In Grades 9 – 12, all students should:

- Develop fluency in operations with real numbers, vectors, and matrices, using mental computations or paper-and-pencil computations for simple cases and technology for more-complicated cases (IC1);
- Judge the reasonableness of numerical computations and their results (IC2).

II. Measurement

A. Understand measurable attributes of objects and the units, systems, and processes of measurement.

In Grades 9 – 12, all students should:

- Make decisions about units and scales that are appropriate for problem situations involving measurement (IIA1).

B. Apply appropriate techniques, tools, and formulas to determine measurements.

In Grades 9 – 12, all students should:

- Analyze precision, accuracy, and approximate error in measurement situations (IIB1);
- Understand and use formulas for the area, surface area, and volume of geometric figures, including cones, spheres, and cylinders (IIB2);
- Apply informal concepts of successive approximation, upper and lower bounds, and limit in measurement situations (IIB3);
- Use unit analysis to check measurement computations (IIB4).

III. Geometry

A. Analyze characteristics and properties of two- and three-dimensional geometric shapes and develop mathematical arguments about geometric relationships.

In Grades 9 – 12, all students should:

- Analyze properties and determine attributes of two- and three-dimensional objects (IIIA1).
- Explore relationships (including congruence and similarity) among classes of two- and three-dimensional geometric objects, make and test conjectures and them, and solve problems involving them (IIIA2);
- Establish the validity of geometric conjectures using deduction, prove theorems, and critique arguments made by others (IIIA3);
- Use trigonometric relationships to determine lengths and angle measures (IIIA4).

B. Specify locations and describe spatial relationships using coordinate geometry and other representational systems.

In Grades 9 – 12, all students should:

- Use Cartesian coordinates and other coordinate systems, such as navigational, polar, or spherical systems, to analyze geometric situations (IIIB1);
- Investigate conjectures and solve problems involving two- and three-dimensional objects represented with Cartesian coordinates (IIIB2).

C. Apply transformations and use symmetry to analyze mathematical situations.

In Grades 9 – 12, all students should:

- Understand and represent translations, reflections, rotations, and dilations of objects in the plane by using sketches, coordinates, vectors, function notation, and matrices (IIIC1);
- Use various representations to help understand the effects of simple transformations and their compositions (IIIC2).

D. Use visualizations, spatial reasoning, and geometric modeling to solve problems.

In Grades 9 – 12, all students should:

- Draw and construct representations of two- and three- dimensional geometric objects using a variety of tools (IIID1);
- Visualize three-dimensional objects from different perspectives and analyze their cross sections (IIID2);
- Use vertex-edge graphs to model and solve problems (IIID3);
- Use geometric models to gain insights into, and answer questions in, others of mathematics (IIID4);
- Use geometric ideas to solve problems in, and gain insights into, other disciplines and other areas of interest such as art and architecture (IIID5).

IV. Data Analysis and Probability

A. Formulate questions that can be addressed with data and collect, organize, and display relevant data to answer them.

In Grades 9 – 12, all students should:

- Understand the difference among various kinds of studies and which types of inferences can legitimately be drawn from each (IVA1);
- Know the characteristics of well-designed studies, including the role of randomization in surveys and experiments (IVA2);
- Understand the meaning of measurement data and categorical data, of univariate and bivariate data, and of the term variable (IVA3);
- Understand histograms, parallel box plots, and scatterplots and use them to display data (IVA4);
- Compute basic statistics and understand the distinctions between a statistic and a parameter (IVA5).

B. Select and use appropriate statistical methods to analyze data.

In Grades 9 – 12, all students should:

- For univariate measurement data, be able to display the distribution, describe its shape, and select and calculate summary statistics (IVB1);
- For bivariate measurement data, be able to display a scatterplot, describe its shape, and determine regression coefficients, regression equations, and correlation coefficients using technological tools (IVB2);

- Display and discuss bivariate data where at least one variable is categorical (IVB3);
- Recognize how linear transformations of univariate data affect shape, center, and spread (IVB4);
- Identify trends in bivariate data and find functions that model the data or transform the data so that they can be modeled (IVB5).

C. Develop and evaluate inferences and predictions that are based on data.

In Grades 9 – 12, all students should:

- Use simulations to explore the variability of sample statistics from a known population and to construct sampling distributions (IVC1);
- Understand how sample statistics reflect the values of population parameters and use sampling distributions as the basis for informal inference (IVC2);
- Evaluate published reports that are based on data by examining the design of the study, the appropriateness of the data analysis, and the validity of conclusions (IVC3);
- Understand how basic statistical techniques are used to monitor process characteristics in the workplace (IVC4).

D. Understand and apply basic concepts of probability.

In Grades 9 – 12, all students should:

- Understand the concepts of sample space and probability distribution and construct sample spaces and distributions in simple cases (IVD1);
- Use simulations to construct empirical probability distributions (IVD2);

- Compute and interpret the expected value of random variables in simple cases (IVD3);
- Understand the concepts of conditional probability and independent events (IVD4);
- Understand how to compute the probability of a compound event (IVD5).

V. Algebra

A. Understand patterns, relations, and functions.

In Grades 9 – 12, all students should:

- Generalize patterns using explicitly defined and recursively defined functions (VA1).
- Understand relations and functions and select, convert flexibly among, and use various representations for them (VA2).
- Analyze functions of one variable by investigating rates of change, intercepts, zeros, asymptotes, and local and global behavior (VA3);
- Understand and perform transformations such as arithmetically combining, composing, and inverting commonly used functions, using technology to perform such as operations on more-complicated symbolic expressions (VA4);
- Understand and compare the properties of classes of functions, including exponential, polynomial, rational, logarithmic, and periodic functions (VA5);
- Interpret representations of functions of two variables (VA6).

B. Represent and analyze mathematical situations and structures using algebraic symbols.

In Grades 9 – 12, all students should:

- Understand the meaning of equivalent forms of expressions, equations, inequalities, and relations (VB1);
- Write equivalent forms of equations, inequalities, and systems of equations and solve them with fluency – mentally or with paper and pencil in simple cases and using technology in all cases (VB2);
- Use symbolic algebra to represent and explain mathematical relationships (VB3);
- Use a variety of symbolic representations, including recursive and parametric equations, for functions and relations (VB4);
- Judge the meaning, utility, and reasonableness of the results of symbol manipulations, including those carried out by technology (VB5).

C. Use mathematical models to represent and understand quantitative relationships.

In Grades 9 – 12, all students should:

- Identify essential quantitative relationships in a situation and determine the class or classes of functions that might model the relationships (VC1);
- Use symbol expressions, including iterative and recursive forms, to represent relationships arising from various contexts (VC2);
- Draw reasonable conclusions about a situation being modeled (VC3).

D. Analyze change in various contexts.

In Grades 9 – 12, all students should:

- Approximate and interpret rates of change from graphical and numerical data (VD1).