

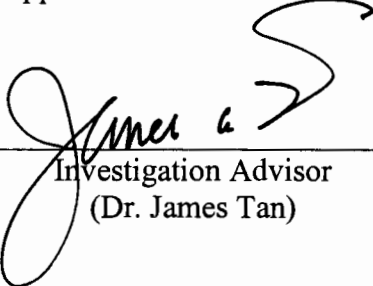
USING THE ACT TO PREDICT COLLEGE GRADUATION

by

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Abstract

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The current study constructs six binary logistic regression models: two sets of models using either (1) high school class size and percentile ranking, and four ACT Test scores (English, Mathematics, Science, and Reading), or (2) high school class size and percentile ranking, and ACT Composite score. For each set, the event was defined at graduating within four, five, or six years of matriculating into the university. Then, ability of the six models to predict graduation within the specified timeframe is assessed.

Table of Contents

Abstract	ii
Chapter I: Introduction.....	1
Purpose of the Study	1
Chapter II: Literature Review	2
Standardized Individual Testing	2
Standardized Group Testing	3
The Evolution of the SAT: Group Testing Changes Academia	4
Scholastic Aptitude Test	5
The ACT Assessment Program: An Alternative to the SAT	7
Noncognitive Components	7
Cognitive Components	9
Form Development and Equating	15
Effects of Coaching.....	16
Aptitude vs. Achievement Tests	16
Chapter III: Methodology	18
Description of Sample.....	18
Measures	18
High School Measures	18
ACT Assessment Measures	20
College Measures.....	20
Chapter IV: Results.....	22
Group Differences.....	22
Females vs. Males.....	22

Graduates vs. Non-Graduate.....	22
Logistic Regression.....	23
Within Model Comparisons.....	24
Overall Comparison of the Six Binary Logistic Regression Models.....	28
Chapter V: Discussion	30
Group Differences.....	30
Logistic Regression.....	31
Limitations	31
References.....	33

List of Tables

Table 1: Enrollment and Graduation Year-Term Breakdown	36
Table 2: Demographical Breakdown	38
Table 3: Means and Standard Deviations of, and Correlations Among High School Variables	39
Table 4: Means and Standard Deviations of, and Correlations Among ACT Variables	40
Table 5: Cross-Tabulation of Time to Graduation and Cohort Year	41
Table 6: Means and Standard Deviations of, and Correlations Among College Variables.....	42
Table 7: High School Variables correlated with ACT Variables	43
Table 8: Gender Differences-Descriptive Statistics.....	44
Table 9: Gender Differences-Analysis of Variance.....	46
Table 10: Graduate/Non-Graduate Group Differences-Descriptive Statistics.....	48
Table 11: Graduate/Non-Graduate Group Differences-Analysis of Variance.....	50
Table 12: Predictor Analysis Results for 4-Year Component Model	52
Table 13: Overall Model Evaluation for 4-Year Component Model.....	53
Table 14: Model Summary for 4-Year Component Model	54
Table 15: Classification Tables for 4-Year Component Model.....	55
Table 16: Predictor Analysis Results for 4-Year Composite Model	56
Table 17: Overall Model Evaluation for 4-Year Composite Model	57
Table 18: Model Summary for 4-Year Composite Model.....	58
Table 19: Classification Tables for 4-Year Composite Model	59
Table 20: Predictor Analysis Results for 5-Year Component Model	60
Table 21: Overall Model Evaluation for 5-Year Component Model.....	61

Table 22: Model Summary for 5-Year Component Model	62
Table 23: Classification Tables for 5-Year Component Model.....	63
Table 24: Predictor Analysis Results for 5-Year Composite Model	64
Table 25: Overall Model Evaluation for 5-Year Composite Model	65
Table 26: Model Summary for 5-Year Composite Model.....	66
Table 27: Classification Tables for 5-Year Composite Model	67
Table 28: Predictor Analysis Results for 6-Year Component Model	68
Table 29: Overall Model Evaluation for 6-Year Component Model.....	69
Table 30: Model Summary for 6-Year Component Model	70
Table 31: Classification Tables for 6-Year Component Model.....	71
Table 32: Predictor Analysis Results for 6-Year Composite Model	72
Table 33: Overall Model Evaluation for 6-Year Composite Model	73
Table 34: Model Summary for 6-Year Composite Model.....	74
Table 35: Classification Tables for 6-Year Composite Model	75
Table 36: Comparison of Classification Tables.....	76
Table 37: Area under the curve for Block 2 of each Model	78

List of Figures

Figure 1: Time to Graduation (Population)79

Figure 2: ROC Curves for all models80

Chapter I: Introduction

Purpose of the Study

In addition to describing the relations among demographic variables, high school variables, ACT variables, and College variables, this study will determine the utility of pre-college variables in predicting the likelihood of graduating from University of Wisconsin-Stout within 4-, 5-, and 6-years of matriculation. Additionally, the institutional graduate rate will be calculated for 4-, 5-, and 6-years of matriculation. Preliminary analysis of the population (see Figure 1) showed that 98% of students were graduated prior to their seventh year.

Chapter II: Literature Review

Standardized Individual Testing

In 1904, the French Ministry of Education assigned Alfred Binet with the task of identifying school children who, for mental ability reasons, were less likely to gain from customary public education; moreover, Binet was to identify which of these children were more likely to gain from special education (Murphy & Davidshofer, 2001). During the next year, Binet and his research assistant, Theodore Simon, developed the Binet-Simon Test, a 30-item test to measure mental ability (Goodwin, 1999; Murphy & Davidshofer, 2001). The test items were arranged in order of increasing difficulty from the simple task of visually tracking an object to more complex tasks such as defining a set of abstract items. The Binet-Simon Test was first revised in 1908 with items being added, modified, and removed resulting in a 58-item test; the way scores were determined also changed. For the 1905 version, the test-taker's age was not included in determining a person's score despite the strong relationship between mental ability and age (Murphy & Davidshofer, 2001). The 1908 version, scores were reported as *mental age*; a person's score was compared to benchmark scores by age. For example, if a 12-year-old scored a 10, they performed at a level typically observed with 10-year-olds (below average); a score of 14 would be typical of 14-year-olds (above average); and a score of 12 would indicate the child was performing at the expected level of typical 12-year-olds (Murphy & Davidshofer, 2001).

To use the Binet-Simon Intelligence Scale in the United States, Stanford University's Lewis Terman developed the Stanford-Binet in 1916 (Walsh & Betz, 2001). To address the ambiguity of what a mental age score actually meant in relation to chronological age, the Stanford-Binet used an *Intelligence Quotient* or *IQ* (Murphy & Davidshofer, 2001). A person's IQ was calculated by dividing mental age by chronological age and multiplying by 100 (to

remove decimals). Using the three examples from above, the 12 year-old's IQ would be 83, 100, and 117 for mental age scores of 10, 12, and 14, respectively. In a 1937 revision, Terman and colleague Maude Merrill developed two alternate forms—Form L and Form M (Walsh & Betz, 2001). A 1960 revision of the test merged the best items from these two forms into one form—Form L-M—which was re-standardized in 1972 (Walsh & Betz, 2001).

The Stanford-Binet: Fourth Edition, the result of a 1985 revision, is still being used (Walsh & Betz, 2001). The Mental Age/Chronological Age method of calculating IQ has been abandoned for a method in which a deviation IQ is calculated. The raw scores are converted to a standard score and then transformed to a score on a scale with a mean of 100 and a standard deviation of 15 (Murphy & Davidshofer, 2001; Nunnally & Bernstein, 1994).

Standardized Group Testing

One of the limitations of individually-administered tests is the amount of time required to test a large number of people. The United States faced this problem during the onset of World War I; with a surge of recruits, the armed forces needed a way to quickly classify enlistees. The American Psychological Association contributed to the war effort by forming a committee, headed by Robert Yerkes, to develop a standardized group test designed to assess its soldiers' mental ability; the result was the Army Alpha and Army Beta tests (Yerkes, 1918).

The Army Alpha test was a written test administered to groups of literate recruits (Murphy & Davidshofer, 2001). The eight subtests of the Army Alpha test included the Commands Test, Arithmetic Problems, Practical Judgment, Synonym-Antonym, Disarranged Sentences, Number Series Completion, Analogies, and Information (Yerkes, 1921). Recruits taking the Army Alpha were told the test was intended to assess how well soldiers remember, think, and follow orders. The test-takers were explicitly told that the administrators were "not

looking for crazy people,” but what position each recruit is “best-fitted” for (Yoakum & Yerkes, 1920, p. 53; as cited in Goodwin, 1999).

In contrast, the Army Beta test was designed for illiterate or non-English-speaking recruits (Murphy & Davidshofer, 2001). The seven subtests of the Army Beta included Maze Test, Cube Analysis, X-O Series, Digit-Symbol, Number Checking, Pictorial Completion, and Geometrical Construction (Yerkes, 1921). Recruits taking the Army Beta received minimal instructions, which included being told not to ask questions, and were given no explanation as to the purpose of the test (Yoakum & Yerkes, 1920 as cited in Goodwin, 1999). Originally, recruits failing the Army Alpha test were to be given the Army Beta test, and those failing the Army Beta test were to be tested individually; however, due to time constraints and logistical problems, the retesting of failing recruits was entirely abandoned.

While nearly two million recruits took the Army Alpha/Army Beta tests, World War I ended before these tests could be used effectively in placing recruits (Goodwin, 1999). At the time, these tests had been perceived as being useful in the “rough classification” of a large number of recruits (Murphy & Davidshofer, 2001, p. 32). While the military received little help from the Army Alpha/Army Beta tests, these tests helped set the framework for large-scale testing in the United States (Goodwin, 1999). Indeed, the idea that one could quickly and fairly accurately assess people’s mental ability was noticed by business and academic institutions (Murphy & Davidshofer, 2001).

The Evolution of the SAT: Group Testing Changes Academia

Upon becoming the president of Harvard in 1933, James Bryant Conant established a scholarship to allow students from comparatively atypical backgrounds to attend the university (Lemann, 1999; Tellez, 2001). Conant was despondent with the aristocracy of the country and

devised the scholarship as a way to replace it with a meritocracy (Lemann, 1999). The scholarship was Conant's attempt to replace what Thomas Jefferson called the artificial aristocracy—based solely on birth and wealth—with a natural aristocracy—based on virtue and talent (Lemann, 1999). Conant's objective was not to grant everyone an opportunity to a college education, but rather to ensure that only the best students were selected for college educations; indeed, Conant was opposed to the G.I. Bill since it offered all veterans an opportunity to attend college (Lemann, 1999; Tellez, 2001). To properly distribute these scholarships, Conant enlisted the services of Wilbur Bender and Henry Chauncey (Lemann, 1999).

Bender, and Conant himself, was they type of person that Conant's scholarship program hoped to identify: hard-working, serious scholars (Lemann, 1999). Chauncey, in contrast, was a typical Harvard student whose lineage could be drawn to Charles Chauncey, who served as Harvard's second president from 1654-1672 (Lemann, 1999; Harvard, 2004). Chauncey was first exposed to mental testing at in the 1920s at Ohio State where he was enrolled in the "elite track" (Tellez, 2001, p. 249). Apparently Chauncey, who had used the prestige of his father and his own athletics to slip in to the university's program, developed distaste for the artificial aristocracy and was eager to abolish it (Tellez, 2001). Chauncey and Bender discovered a test developed by Carl Brigham, who helped Yerkes develop the Army Alpha and Army Beta tests (Lemann, 1999).

Scholastic Aptitude Test

In 1926 Brigham began experimenting with his version of the Army Alpha/Army Beta tests in academic settings (Lemann, 1999; PBS, 1999). At the time the Army Tests were being developed, Brigham was a strong believer in the eugenics movement, but by the time Chauncey and Bender came to Princeton for Conant's scholarship, he all but gave up on eugenics and IQ,

but not on the SAT (Goodwin, 1999; Lemann, 1999; PBS, 1999). Chauncey felt Brigham's SAT was the key to objectively and systematically selecting students for Conant's Harvard scholarship program (Lemann, 1999; Tellez, 2001). Conant had only one reservation with the SAT: he wanted a test that measured intelligence, not the educational quality received, which Chauncey assured it did; the SAT was adopted for selecting Conant's scholarship students (Lemann, 1999).

At the onset of the Second World War, Conant and Chauncey established their testing system; once Japan brought the US into the war, essay entrance exams were suspended and replaced with the SAT for all incoming students, not just the scholarship students (Lemann, 1999). Brigham, who opposed the formation of a testing organization that was funded by the test-takers warning that attention would shift from improving tests to promoting them, died on January 24, 1943 (Lemann, 1999; PBS, 1999). Once again, testing was used for the war effort; on April 2, 1943, the Army-Navy College Qualifying Test—a version of the SAT adapted for officer selection—was administered nationwide to over 316,000 high school seniors proving that coordinated group testing was possible (PBS, 1999; Lemann, 1999).

After the end of the war, Conant managed to organize the top educational testing organizations into a single entity which, in 1948, became the Educational Testing Service (ETS; PBS, 1999; Lemann, 1999). That same year, ETS established a Berkley, California office and slowly but surely, universities across the country began requiring applicants to take the SAT. By 1960, the elite University of California system had done so (PBS, 1999; Lemann, 1999). In 1994, the Scholastic Aptitude Test was renamed the Scholastic Assessment Test, but now prefers to use just the initials SAT (Lehman, 1999).

The ACT Assessment Program: An Alternative to the SAT

In 1959, the American College Test (ACT) Assessment Program emerged from the University of Iowa as an alternative to the SAT.

The ACT Assessment was developed from the work of E. F. Lindquist who determined that the most effective way to assess a student's preparedness for college was to measure their mastery of knowledge and skills, both of which are required college success (ACT, 2003b).

Noncognitive Components

Upon registration for the ACT Assessment, test takers are asked to complete several noncognitive components. These components collect information regarding courses taken in high school, grades earned, interests, and a student profile. While test takers are not required to complete these sections to take the ACT, they are strongly encouraged to do so in order to provide college admission offices with the most complete information. Since non-cognitive information was not available for the current study, only a brief description follows; for a more detailed description of each section, see the *User Handbook: 2003-2004* (ACT, 2003b).

High school course/grade information. Starting in 1985, the ACT Assessment started collecting high school course grades to better predict college success. From a list of 30 courses, test takers are asked to indicate whether they have previously taken, are currently taking, have not taken but plan to take, or have not taken and do not plan to take each course. If test takers indicate that they have previously taken or are currently taking the course, they are asked to mark the grade they earned or expect to earn in the course.

With self-reported grades for relatively high-stakes testing, one might expect artificially inflated grade information to be reported. The ACT assessed the accuracy of the information collected on the High School Course/Grade Information section and found that 87% of the 1,074

sampled test takers reported accurate information (Sawyer, Laing, & Houston, 1988). Many discrepancies were due to omissions or misinterpretation of the transcripts; indeed, 71% of the self reports matched exactly and 97% were within one letter grade.

Interest inventory. This section of the non-cognitive component presents 90 statements describing various activities (e.g., writing short stories, explaining legal rights to people, assembling a cabinet from written instructions, and designing a poster for an event) to the student, who is asked to indicate their level of inclination for each activity (*Like*, *Neutral*, or *Dislike*). The test takers are explicitly instructed to make their choices based on their desire to do the activities, not on their ability to do them. Test takers are also asked to avoid central tendency by answering *Like* or *Dislike* to as many activity items as possible. The premise for collecting these data is to provide test takers with college programs and occupations that closely match to their interests, which they may not have otherwise considered.

Student profile section. This section is designed as a self-assessment of test takers' educational plans. This section consists of 186 items and collects information from the following eleven areas: (1) Admission/Enrollment Information; (2) Educational Plans, Interests, and Needs; (3) Special Educational Needs, Interests, and Goals; (4) College Extracurricular Plans; (5) Financial Aid; (6) Background Information; (7) Factors Influencing College Choice; (8) High School Information; (9) High School Extracurricular Activities; (10) Out-of-Class Accomplishments; and (11) Evaluation of High School Experience.

The data from these non-cognitive sections are collected and submitted along with the test scores to the colleges the test taker indicates. The college's admissions office may then use this information in the application process.

Cognitive Components¹

The ACT Assessment Program was designed to assess the test taker's mastery of four areas: English, Mathematics, Reading, and Science Reasoning; each of which is represented by a separate component test. ACT scores are based on the number of items test taker answer correctly; there is no penalty for guessing on items. In fact, the ACT encourages test takers to answer every question on the test, even if it means guessing.

English Test. The English Test is a 45-minute, 75-item test that assesses test takers' rhetorical skills and understanding of rules used in the English language. Spelling, vocabulary, and rules of grammar are not included in this test. The English Test has a reliability estimate of 0.91 (ACT, 1997 as cited in Walsh & Betz, 2001).

Students are asked to read a set of five prose passages and complete sets of multiple-choice questions related to each prose passage. Some of the items ask test-takers to replace underlined portions of passages with alternate portions. Other items ask about specific sections of passages or the entire passage where students must select the most appropriate response; for such items, the lines and paragraphs are numbered for reference. For many of the items in the English Test, test-takers have a response option to keep the referent portion of the passage the same (i.e., "NO CHANGE").

In addition to the total score based on all 75 items, two sub-scores are reported: a Usage/Mechanics score based on a set of 40 items, and a Rhetorical Skills score based on the remaining set of 35 items.

The item set reflecting usage and mechanics focuses on the three content areas: Punctuation (10 items), Grammar and Usage (12 items), and Sentence Structure (18 items). The

¹ Unless otherwise noted, the descriptions of the four component tests are based on *User's Handbook: 2003-2004* (ACT 2003b).

Punctuation content items focus on the punctuation within sentences and at the end of them. These items emphasize the relation between punctuation and sentence meaning. For example, how punctuation is used to avoid vagueness or how punctuation can indicate apposition. The Grammar and Usage content items focus on the agreement between subject and verbs, pronoun and antecedent, and modifiers and their targets; the formation of verbs, comparative and superlative adjectives and adverbs; pronoun use; and natural use of the language. The Sentence Structure content items assess student's comprehension of the relation between and among clauses, modifier placement, and alterations of sentence structure.

The item set reflecting Rhetorical Skills also focuses on three content areas: Strategy (12 items), Organization (11 items), and Style (12 items). The Strategy content items assess student's ability to choose appropriate expressions, assess the effects of adding, removing, or altering statements, and selecting appropriate introductory, transition, and closing statements in order to develop a topic. Somewhat related, the Organization content items assess student's ability to organize an argument and assess the relevance of statements. Finally, the Style content items assess student's ability to select the best words and graphics in arguments, manage portions of statements for effectiveness in arguments, avoid ambiguity in arguments, and maintain a consistent tone throughout arguments.

Mathematics Test. The Mathematics Test is a 60-minute, 60-item test designed to assess test-taker's mathematical skills. The content of this test is limited to skills acquired in typical math courses taken through the end of a high school student's junior year. The Mathematics Test has a reliability estimate of 0.91 (ACT, 1997 as cited in Walsh & Betz, 2001).

Most questions in the Mathematics Test are unrelated to others; however, some sets of questions rely on the same information source (e.g., a graph or a chart). It is assumed that test-

takers have knowledge of basic mathematical formulas and computational skills. While calculators are permitted for this test, these must meet ACT requirements and cannot be shared (see *User Handbook: 2003-2004*, ACT 2003b for details).

Items in the Mathematics Test cover four cognitive areas: Knowledge and Skills, Direct Application, Understanding Concepts, and Integrating Conceptual Understanding. Items in the Knowledge and Skills cognitive area assess test-taker's ability to solve problems presented in mathematical terms. Items in the Direct Application cognitive area assess test-taker's ability to solve problems presented in simple terms and in real-world examples. The third area covered, Understanding Concepts, measures test-taker's ability to understand major concepts to reach an inference or conclusion. The final cognitive area covered by the Mathematics Test, Integrating Conceptual Understanding, assesses test-taker's ability to integrate two or more concepts to derive conclusions from non-routine problems.

In addition to a total score based on all 60 items, three sub-scores are reported for the Mathematics Test: a Pre-Algebra/Elementary Algebra score based on a set of 24 items, an Intermediate Algebra/Coordinate Geometry score based on a set of 18 items, and a Plane Geometry/Trigonometry score based on the remaining set of 18 items.

The Pre-Algebra/Elementary Algebra item set consists of questions regarding pre-algebra (14-items) and questions regarding elementary algebra (10-items). Pre-algebra items "are based on basic operations using whole numbers, decimals, fractions, and integers; place value; square roots and approximations; the concept of exponents; scientific notation; factors; ratio, proportion, and percent; linear equations in one variable; absolute and ordering numbers by value; elementary counting techniques and simple probability; data collection, representation, and interpretation; and understanding simple descriptive statistics." Items in the Elementary Algebra

content area “are based on properties of exponents and square roots, evaluation of algebraic expressions through substitution, using variables to express functional relationships, understanding algebraic operations, and the solution of quadratic equations by factoring” (ACT, 2003b, p. 3).

The Intermediate Algebra/Coordinate Geometry item set consists of questions regarding Intermediate Algebra (9 items) and Coordinate Geometry (9 items). Intermediate Algebra items “are based on an understanding of the quadratic formula, rational and radical expressions, absolute value equations and inequalities, sequences and patterns, systems of equations, quadratic inequalities, functions, modeling, matrices, roots of polynomials, and complex numbers.” Coordinate Geometry items “are based on graphing and the relations between equations and graphs, including points, lines, polynomials, circles, and other curves; graphing inequalities; slope; parallel and perpendicular lines; distance; midpoints; and conics” (ACT, 2003a, p. 7).

The Plane Geometry/Trigonometry item set consists of questions regarding Plane Geometry (14 items) and Trigonometry (4 items). Plane Geometry items “are based on the properties and relations of plane figures, including angles and relations among perpendicular and parallel lines; properties of circles, triangles, rectangles, parallelograms, and trapezoids; transformations; the concept of proof and proof techniques; volume; and applications of geometry to three dimensions.” Trigonometry items “are based on understanding trigonometric relations in right triangles; values and properties of trigonometric functions; modeling using trigonometric functions; use of trigonometric identities; and solving trigonometric equations.” (ACT, 2003a, p. 8).

Reading Test. The Reading Test is a 35-minute, 40-item test designed to assess the test-taker's comprehension of text as the result of skill in referencing and rationale. The items require the test-takers to draw meaning from multiple texts by referring to explicit text, by generating implicit meaning, and by drawing conclusions, comparisons, and generalizations. The Reading Test has a reliability estimate of 0.86 (ACT, 1997 as cited in Walsh & Betz, 2001).

The test-taker must read a set of four prose passages on topics typical to content that college freshman are exposed to (these passages are numbered for reference). The topics range from Prose Fiction to Humanities and from Social Studies to Natural Sciences. For each set of passages, there are sets of multiple-choice items for the user to select the best answer from. Each passage and related items are independent and exclude facts exterior to the passages, isolated vocabulary, and conventions of logic.

Two skill sets, Referring Cognitive Skills and Reasoning Cognitive Skills, are being measured in the Reading Test. Referring Cognitive Skills refer to the ability of test-takers to recognize explicitly stated main ideas, details, and relationships. Reasoning Cognitive Skills assess to the ability of test-takers to infer main ideas and relationships, to demonstrate comprehension of the text, and determine meanings of words and phrases in context.

In addition to the total score based on all 40 items, two sub-scores are also reported: a Social Studies/Science score based on a set of 20 items, and an Arts/Literature score based on the remaining set of 20 items.

The Social Studies/Science item set focuses on two content areas: Social Studies (10 items) and Natural Sciences (10 items). The Social Studies items “are based on passages in the content areas of anthropology, archaeology, biography, business, economics, education, geography, history, political science, psychology, and sociology” (ACT, 2003a, p. 8). The

Natural Sciences content items “are based on passages in the content areas of anatomy, astronomy, biography, botany, chemistry, ecology, geology, medicine, meteorology, microbiology, natural history, physiology, physics, technology, and zoology” (ACT, 2003a, p. 8).

The Arts/Literature item set focuses on two content areas: Prose Fiction (10 items) and Humanities (10 items). The Prose Fiction content items “are based on intact short stories or excerpts from short stories or novels” (ACT, 2003a, p. 8). The Humanities content items “are based on passages from memoirs and personal essays and in the content areas of architecture, art, dance, ethics, film, language, literary criticism, music, philosophy, radio, television, and theater” (ACT, 2003a, p. 8).

Science Test. The Science Test is a 35-minute, 40-item tests designed to assess the student’s ability to interpret, analyze, evaluate, reason, and solve problems; calculators are not permitted on this test. Unlike the previous three tests, this test has three different item formats: Data Representation, Research Summaries, and Conflicting Viewpoints. The Science Test has a reliability estimate of 0.84 (ACT, 1997 as cited in Walsh & Betz, 2001).

In the first format, Data Representation, information is conveyed in graphs, charts, scatterplots, and tables. Items presented in this format assess student’s ability to read and understand graphical and tabular information sources as is commonly displayed in scientific journals and books. For the next format, Research Summaries, information is provided as a brief fictitious description of an experiment. Items presented in this format focus on the experimental design and results presented. Conflicting Viewpoints, the final format, presents the user with multiple arguments that are inconsistent with one another with each argument being based on

alternative hypotheses or from partial data sources. Items presented in this format require test takers to comprehend, evaluate, and compare these alternate viewpoints.

While only a single score based on all 40 items is reported for the Science Test, the items come from four different content areas (Biology, Chemistry, Physics, and Earth/Space Sciences). The Science Test items are presented in such a way that at least one passage, but not more than two passages are from each content area for each format.

ACT reports a composite reliability estimate of .96 and an estimated reliability range of .64 to .86 for their sub-scores (e.g., Usage/Mechanics, Plane Geometry/Trigonometry, and Arts/Literature) across five forms. The standard error of measurement across the same five forms ranged from 0.87 to 0.92 points for the composite score, from 1.4 to 2.3 points for each of the four tests, and from 1.1 to 1.9 points for each of the sub-scores (ACT, 2003b; see also ACT 1997 for more detailed information on reliability).

Form Development and Equating

In order to maintain the statistical validity of these high-stakes tests, new forms must be developed continuously. Unique content is developed for each national administration date to prevent test takers from artificially inflating their scores from advanced knowledge of test items. For example, if a student takes the ACT in their junior year of high school and again in their senior year, the items in each test will be different. The only benefit of retesting is that the test-taker will be familiar with the structure and the style of the test items.

ACT Assessment develops multiple new forms of the ACT Assessment each year, with each form taking about thirty months to fully develop. Each individual question is put through rigorous scrutiny to ensure the item is accurate, appropriate, and fair. These items are administered to a sample of students taking the ACT Assessment. While the scores on the

equating section are not counted toward the test-taker's final score; instead, each development item is equated with their score on the remaining items. The development items that performed at an acceptable level then go through several rounds of staff review and are submitted for review by several ACT-independent groups (e.g., consultants, teachers, and curriculum specialists). These independent reviewers then meet with ACT staff for the preparation of the new forms. Each item that appears in these national test forms is subjected to at least twenty independent reviews.

Effects of Coaching

The idea that student's can improve their scores on standardized test such as the ACT and SAT is widely accepted; however, the degree of this improvement is still under debate (Anastasi, 1981; Briggs, 2001; Murphy & Davidshofer, 2001). Commercial test preparation companies (such as Kaplan) report improvements of up to 100 points (one standard deviation) on the SAT and private tutors report even greater improvements, as much as 200 points (Briggs, 2001). With charges ranging from \$700 to \$3,000 for commercial programs and up to \$450 an hour for private tutors (Briggs, 2001), the test preparation business has become a cottage industry. While researchers are not in agreement on the extent of improvement coaching programs offer, there does seem to be agreement in the idea that such improvements are marginal for the average test-taker (Alderman & Powers, 1980; Briggs, 2001; Powers, 1993; Powers & Rock, 1999).

Aptitude vs. Achievement Tests

Tests can be broken into two main types: aptitude tests and achievement tests. Whereas aptitude tests are typically general in content that may be learned over long time spans, achievement tests focus on specific content that must be mastered in a restricted time span (Murphy & Davidshofer, 2001). In addition to the content and time span differences, the typical

uses of these two types also tend to differ, although each type may serve both purposes. Because of their focused content, achievement tests tend to be used to assess material mastery; for example, the ACT and final exams in high school and college courses are used to assess how well students have mastered the content (Murphy & Davidshofer, 2001). Aptitude tests on the other hand, assess more generalized knowledge and skill sets; for example, the SAT would be considered an aptitude test since it attempts to predict future academic behavior based on what students have learned and mastered throughout their educational careers (Murphy & Davidshofer, 2001; see also Cronbach, 1990 for more discussion on this issue).

Chapter III: Methodology

Description of Sample

The Admissions Office of the University of Wisconsin-Stout maintains a database of records for all admissions made since Fall term, 1994. During Spring term, 2003, this database was queried for records of all students admitted prior to this point, resulting in a population of 11,877 admission records. Preliminary analysis (see Figure 1) showed that the vast majority of the graduated population had graduated prior to their 7th year. As a result, only students with at least six full years between their matriculation date and the query date were included for further analysis. The resulting sample, enrolled between fall 1994 and fall 1998, totaled 6,414 admission records.

The mean age of the sample was 18.93 years (SD = 2.35 years). Gender was fairly evenly split with 51.4% male and 48.6% female. The sample was predominantly White (95.2%) with Asian Americans being the largest minority group (1.9%). The remaining ethnicities were as follows: Hispanic/Latino (0.7%), African American (0.6%), and Native American (0.6%). One percent of the sample was listed as *Alien/Unknown*.

Table 1 shows Fall terms corresponded to the vast majority of enrollments. The Fall term enrollment figures steadily increase from 1994 ($n = 1,075$) through 1998 ($n = 1,347$). Table 1 also shows the graduation dates for the 35.4% of the sample that graduated by the end of Fall term, 2002.

Measures

High School Measures

Consider three students with different ordinal rankings from different high schools; the first student ranked 37th in a class of 75, the second ranked 79th in a class of 150, and the third

ranked 60th in a class of 300. Using just these numbers, it is difficult to gauge their performance; while the first student had the best ordinal ranking of the three, they also came from the smallest class. Likewise, the third student had the median ordinal ranking, but came from the largest class. In order to compare students from different high schools, and therefore different class sizes and ordinal ranking, a third variable, Percentile Rank, was created by converting each student's ordinal rank into a percentage of students in their class that were at or lower than their ordinal rank using the following formula:

$$\text{Percentile Rank} = \frac{\text{Class Size} - \text{Ordinal Rank}}{\text{Class Size} - 1}$$

where *Percentile Rank* is the referent student's relative rank, *Class Size* is the size of the student's graduating class, and *Ordinal Rank* is the student's standing within their class. Using this formula, a lower percentile rank corresponds to a higher ordinal rank; alternately stated, the closer ordinal rank is to 1, the closer percentile rank will be to 100%. The use of percentile rank allows for information to be conveyed regarding a student's relative ranking independent of the class size. Percentile rank along with class size allows for comparison between students from different graduating classes.

By applying the percentile rank formula to the three student example presented above, we can say for certain that, all other factors being equal, the third student, who had a percentile rank of 80%, out-performed the first student (percentile rank = 51%); the second student (percentile rank = 48%) was out-performed the third student and marginally by the first.

Table 3 shows the significant correlation ($\alpha \leq .01$, two-tailed) ordinal rank had with class size ($r = .77$, $r^2 = .59$) and with percentile rank ($r = -.61$, $r^2 = .38$). Due to this high level of convergence, ordinal rank was not used in the logistic regression models. Percentile rank and class size, while significantly correlated, were relatively unrelated ($r = -.12$, $r^2 = .02$).

ACT Assessment Measures

There were five ACT Assessment-related variables: four component test scores (English, Mathematics, Science, and Reading), and a composite score (arithmetic average of the four component test scores rounded to the nearest whole number). Table 4 shows the means and standard deviations for, and correlations among these five ACT variables. Because the composite score is the arithmetic average of the other tests, the expected convergence with each component test score is observed ($r_s = .72$ to $.83$, $r^2_s = .52$ to $.69$).

While the component tests assess different areas of college readiness, Table 4 also shows relatively high convergence among several tests (e.g., Reading and English $r = .595$, and Reading and Science $r = .660$); however, the content areas they cover also appear to be related. The Mathematics and Reading tests have the least shared variance among all four tests ($r = .36$, $r^2 = .12$). While the data from some of the tests may be closely related to other tests, it is apparent they assess unique areas and are not fully represented by the Composite score. Because the composite score shares anywhere from 52% to 69% of variance with the four test scores, two sets of logistic regression models were constructed: one set using all four ACT component test scores with percentile rank and class size, and the other set using only the ACT composite score with percentile rank and class size.

College Measures

There are three variables related to college performance that are available in the current study (first GPA on record, last GPA on record, and years required to earn degree). Because the current study's focus is on predicting graduation based only on data available at the time of admission, these three college measures were not used in the logistic regression models. Table 5 shows a cross-tabulation of time required to graduate by cohort year. The 4-5 years post

matriculation interval was the most frequent amount of time required with half of the graduating sample graduating during that time frame; the 3-4 year interval was the next most frequent amount of time required with about 38% of the graduating sample graduating in that time frame.

This finding is supported by inspecting Table 6. The mean time to degree for the graduating sample was 4.12 years (SD = 0.67 years); since the distribution for time to degree was fairly normal (SK = .947, SE = .051; KR = 1.519, SE = .103), we can conclude that about 68% of graduating students in the sample are expected to graduate between 3.44 and 4.79 years of matriculating (± 1 standard deviation). Table 6 also shows that the average GPA increased from 2.67 to 2.79 while the standard deviation decreased from 0.71 to 0.66 between students' first recorded GPA and their last recorded GPA.

While high school GPA information was not available for the current study, high school graduating class size and ordinal rank in graduating class were. Hamilton (1990) found a strong negative correlation between high school GPA and high school ordinal rank ($r = -.88$, $r^2 = .78$). With such a large overlap between high school GPA and ordinal rank, we can use percentile rank, which is a function of graduating class size and ordinal rank, as a proxy for high school GPA. Pettijohn (1995) noted that high school GPAs were significantly correlated with first year college GPAs ($r = .62$, $r^2 = .38$); in the current study, percentile rank is significantly correlated with the first college GPA ($r = .48$, $r^2 = .23$). Pettijohn (1995) also reported that high school GPAs were significantly correlated with ACT scores ($r = .41$, $r^2 = .17$), which are significantly correlated with first year college GPAs ($r = .63$, $r^2 = .40$). In the current study, percentile rank was significantly correlated with ACT composite score ($r = .33$, $r^2 = .11$) which was significantly correlated with the first college GPA ($r = .30$, $r^2 = .09$).

Chapter IV: Results

*Group Differences**Females vs. Males*

To address the gender differences raised by Mau and Lynn (2001) and Pettijohn (1995), a one-way analysis of variance (ANOVA) was run comparing males and females on several variables. Table 8 and Table 9 show that males performed significantly better on test-based metrics: higher ACT Mathematics Test score ($F = 332.504, p < .001$), higher ACT Science Test score ($F = 311.386, p < .001$), and higher ACT Composite score ($F = 48.369, p < .001$). Females, conversely, performed significantly better on performance-based metrics: higher percentile rank ($F = 226.003, p < .001$), higher first GPAs ($F = 243.904, p < .001$), higher last GPAs ($F = 280.484, p < .001$), and shorter time required to graduate ($F = 103.906, p < .001$).

Graduates vs. Non-Graduate

To determine if group differences on key variables exist, an ANOVA was again employed comparing graduates and non-graduates. Table 10 and Table 11 show that there was no significant difference found in students' graduating high school class size between the groups. Graduates had a significantly higher percentile rank than non-graduates ($F = 383.950, p < .001$). Graduates earned a higher score on the Mathematics Test ($F = 5.832, p = .016$) while non-graduates earned higher scores on the Reading Test ($F = 6.422, p = .011$). For the English and Science Test and the Composite scores, no significant differences were found. Graduates earned significantly higher first GPAs ($F = 536.651, p < .001$), and higher last GPAs ($F = 1204.966, p < .001$) than non-graduates. Since non-graduates did not earn their degree, it was impossible to detect any differences in the amount of time required to earn a degree.

Logistic Regression

Similar to linear regression, logistic regression provides coefficients for each predictor and a constant. Logistic regression models are described using the following equation:

$$\pi = \frac{e^{\alpha + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k}}{1 + e^{\alpha + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k}}$$

“where π is...the probability of an event, [$e \approx 2.718282$,] α is the Y intercept, β s are regression coefficients, and X s are a set of predictors” (Peng, Lee, & Ingersoll, 2002, p 5). Whereas linear regression can predict a continuous variable, logistic regression predicts the probability (bound by 0 and 1) that an event will occur.

The null hypothesis (H_0) of a binary logistic regression model assumes that all regression coefficients are equal to zero; to reject H_0 at least one of the coefficients must be significantly different from zero. When a model rejects the H_0 , the model is able to predict the event at a greater rate than simply guessing the mode outcome for all cases (Peng et al., 2002).

By applying the following formula to predictor coefficients:

$$\text{Odds Ratio} = e^{\beta}$$

we get the Odds Ratio. The odds ratio represents the change in the probability of the event given a one unit increase in the predictor variable. If the odds ratio is greater than 1.0, higher values of the predictor variable correspond to an increase in the likelihood that an event will occur; if the odds ratio is less than 1.0, lower values of the predictor variable correspond to a decrease in the likelihood than an event will occur. For example, the coefficient for High School Percentile Rank was 0.0267 in the 4-Year Composite Model; the resulting odds ratio was 1.0271, that is, each one point increase in ACT Composite score corresponds to a 1.0271 times greater likelihood of graduating. Using this example, a student with a percentile rank of 82 would be about 15 times

more likely to graduate than a student with a percentile rank of 67 ($e^{0.0267} \times (82 - 67) = 1.0271 \times 15 = 15.4089$).

Using the methods suggested by Wuensch (2004), two sets of three logistic regression models (six total) were built and tested to determine their utility in predicting student graduation within four, five, and six years of matriculation: one set of models using percentile rank and the four ACT component test scores, and the other set of models using percentile rank and the ACT Composite score.

Each of these models was built in three progressive blocks. Block 0, which contains only the constant, which is based simply on the population event rate; for the current study, the overall graduation rate was 35.4% meaning that all cases are predicted to be non-events. Block 1 adds percentile rank to Block 0; since the odds ratios for percentile rank in each of the six models built is greater than 1.0, higher percentile rank values correspond to increased likelihood of graduating. The final block, Block 2, adds either (1) the four ACT component test scores or (2) the composite ACT score to Block1, depending on the model being built.

Within Model Comparisons

4-Year Component Model. Table 12 describes each predictor for each of the three blocks of this model. In all blocks, the constant proved to be a significant factor to the prediction of graduation (χ^2 s = 300.1706, 376.2193, and 35.9535, $ps < .001$ for Blocks 0, 1, and 2 respectively). Percentile Rank contributed significantly to Block 1 ($\chi^2 = 242.3733$, $p < .001$, odds ratio = 1.024), and to Block 2 ($\chi^2 = 245.3670$, $p < .001$, odds ratio = 1.027). ACT Reading was the only other significant contributor to Block 2 ($\chi^2 = 10.2245$, $p = .001$, odds ratio = 0.972); as described above, this means that increases in ACT Reading Test scores correspond to a decreased likelihood of graduation from the University of Wisconsin-Stout.

The overall model evaluations for the 4-Year Component Model is displayed in Table 13. Block 2 was a significant improvement over Block 1 ($\chi^2 = 33.5358, p < .001$). The summaries for this model, displayed in Table 14, show R^2 values for Block 1 of 4.6% and 6.3%; R^2 values for Block 2 are slightly higher at 5.2% and 7.1% (for the Cox and Snell R^2 and Nagelkerke R^2 , respectively).

Table 15 shows the classification tables for the three blocks of this model; Block 0 had an overall correct prediction rate of 61.8%. The inclusion of high school percentile rank (in Block 1) increased the overall correct prediction rate to 62.5%. With the addition of the four ACT Component Test variables as predictors (in Block 2), the overall correct prediction rate increased to 62.7%.

4-Year Composite Model. Table 16 describes each predictor for each of the three blocks of this model. Again, in all blocks, the constant proved to be a significant factor to the prediction of graduation from the University of Wisconsin-Stout (χ^2 s = 379.6400, 468.7742, and 47.7626, p s < .001 for Blocks 0, 1, and 2 respectively). Percentile rank contributed significantly to Block 1 ($\chi^2 = 295.6804, p < .001$, odds ratio = 1.0251) and to Block 2 ($\chi^2 = 312.5059, p < .001$, odds ratio = 1.0283). The ACT Composite score was also a significant contributor to Block 2 ($\chi^2 = 29.1214, p < .001$, odds ratio = 0.9522).

The overall model evaluations for the 4-Year Composite Model are displayed in Table 17. Block 2 was a significant improvement over Block 1 ($\chi^2 = 29.4135, p < .001$). The summaries for this model, displayed in Table 18, show R^2 values of 5.3% and 7.3% for Block 1 and 5.8% and 7.9% for Block 2 (for the Cox & Snell R^2 and Nagelkerke R^2 , respectively).

Table 19 shows the classification tables for the three blocks of this model; Block 0 had an overall correct prediction rate of 62.9%. The inclusion of high school percentile rank (in Block

1) increased the overall correct prediction rate to 63.6%. With the addition of the ACT Composite score (in Block 2), the overall correct prediction rate declined slightly to 63.5%.

5-Year Component Model. Table 20 describes each predictor for each of the three blocks of this model. As with the corresponding 4-Year Model, the constant proved to be a significant factor to prediction of graduation (χ^2 s = 57.6783, 263.0437, and 30.8171, p s < .001 for Blocks 0, 1, and 2 respectively). Percentile rank contributed significantly to Block 1 ($\chi^2 = 221.2456$, $p < .001$, odds ratio = 1.026) and to Block 2 ($\chi^2 = 208.8097$, $p < .001$, odds ratio = 1.027). As before, ACT Reading was the only other significant contributor to Block 2 ($\chi^2 = 13.1001$, $p < .001$, odds ratio = 0.965).

The overall model evaluations for the 5-Year Component Model are displayed in Table 21. Block 2 was a significant improvement over Block 1 ($\chi^2 = 25.7292$, $p < .001$). The summaries for this model are displayed in Table 22. The R^2 values were 5.4% and 7.3% for Block 1 and 6.0% and 8.0% for Block 2 (for the Cox & Snell R^2 and Nagelkerke R^2 , respectively).

Table 23 shows the classification tables for the three blocks of this model; Block 0 had an overall correct prediction rate of 55.8%. The inclusion of high school percentile rank (in Block 1) increased the overall correct prediction rate to 56.6%. With the addition of the four ACT Component scores (in Block 2), the overall correct prediction rate increased to 61.4%.

5-Year Composite Model. Table 24 describes each predictor for each of the three blocks of this model. In all three blocks, the constant proved to be a significant factor in the prediction for graduation from the University of Wisconsin-Stout (χ^2 s = 87.1117, 318.3637, and 32.4616, p s < .001 for Blocks 0, 1, and 2 respectively). Percentile rank contributed significantly to Block 1 ($\chi^2 = 258.2660$, $p < .001$, odds ratio = 1.026) and to Block 2 ($\chi^2 = 266.0653$, $p < .001$, odds ratio

= 1.029, respectively. ACT Composite also contributed significantly to Block 2 ($\chi^2 = 17.2385$, $p < .001$, odds ratio = 0.940).

The overall model evaluations for the 5-Year Composite Model are displayed in Table 25. Block 2 was a significant improvement over Block 1 ($\chi^2 = 17.3495$, $p < .001$). The summaries for this model are displayed in Table 26. The R^2 values were 6.0% and 8.0% for Block 1 and 6.3% and 8.5% for Block 2 (for the Cox & Snell R^2 and Nagelkerke R^2 , respectively).

Table 27 shows the classification tables for the three blocks of this model; Block 0 had an overall correct prediction rate of 57.0%. The inclusion of high school percentile rank (in Block 1) increased the overall correct prediction rate to 57.7%. With the addition of the ACT Composite score (in Block 2), the overall correct prediction rate increased to 61.4%.

6-Year Component Model. Table 28 describes each predictor for each of the three blocks of this model. As with the previous models, the constant proved to be a significant factor to the prediction of graduation in each of the three blocks (χ^2 s = 22.4180, 179.3135, and 25.1732, $ps < .001$ for Blocks 0, 1, and 2 respectively). Percentile rank contributed significantly to Block 1 ($\chi^2 = 161.0753$, $p < .001$, odds ratio = 1.0255) and to Block 2 ($\chi^2 = 144.0434$, $p < .001$, odds ratio = 1.026). ACT Reading was the only other significant contributor to Block 2 ($\chi^2 = 12.1382$, $p < .001$, odds ratio = 0.961).

The overall model evaluation for the 6-Year Component Model are displayed in Table 29. Block 2 was a significant improvement over Block 1 ($\chi^2 = 20.8518$, $p = .001$). Table 30 shows the model summary for this model. The R^2 values were 5.4% and 7.2% for Block 1 and 6.0% and 8.0% for Block 2 (for the Cox & Snell R^2 and Nagelkerke R^2 , respectively).

Table 31 shows the classification tables for the three blocks of this model; Block 0 had an overall correct prediction rate of 54.2%. The inclusion of high school percentile rank (in Block 1) increased the overall correct prediction rate to 56.8%. With the addition of the four ACT Component Test scores (in Block 2), the overall correct prediction rate increased to 61.3%.

6-Year Composite Model. Table 32 describes each predictor for each of the three blocks of this model. In all three blocks, the constant proved to be a significant factor to the prediction of graduation (χ^2 s = 37.4230, 213.9057, and 23.8376, p s < .001 for Blocks 0, 1, and 2 respectively). Percentile rank also contributed significantly to Block 1 ($\chi^2 = 184.8534$, $p < .001$, odds ratio = 1.026) and to Block 2 ($\chi^2 = 186.9207$, $p < .001$, odds ratio = 1.028). ACT Composite was also a significant contributor to Block 2 ($\chi^2 = 9.2956$, $p = .002$, odds ratio = 0.965).

The overall model evaluations for the 6-Year Composite Model are displayed in Table 33. As with all previous models, Block 2 was a significant improvement over Block 1 ($\chi^2 = 9.3316$, $p = .009$). Table 34 shows the model summary for this model. The R^2 values were 5.8% and 7.8% for Block 1 and 6.1% and 8.1% for Block 2 (for the Cox & Snell R^2 and Nagelkerke R^2 respectively).

Table 35 shows the classification tables for the three blocks of this model; Block 0 had an overall correct prediction rate of 55.3%. The inclusion of high school percentile rank (in Block 1) increased the overall correct prediction rate to 57.9%. With the addition of the ACT Composite score (in Block 2), the overall correct prediction rate increased to 60.7%.

Overall Comparison of the Six Binary Logistic Regression Models

Table 36 shows five variables that summarize the six classification tables presented for each block of the six models described above. *Sensitivity* is calculated by dividing the number of observed events that were predicted as such by the total number of observed events; *Specificity* is

calculated by dividing the number of observed nonevents that were predicted as such by the total number of observed nonevents. In other words, *sensitivity* is a measure the ability to correctly predict an event whereas *specificity* is a measure of the ability to correctly predict a nonevent. The *False Positive Rate* is calculated by dividing the number of observed nonevents that were predicted as events by the total number of predicted events; *False Negative Rate* is calculated by dividing the number of observed events that were predicted as nonevents by the total number of predicted nonevents. The *Overall Correct Prediction Rate* is calculated by dividing the total number of correct predictions by the total number of predictions made.

Better models have sensitivity, specificity, and overall correct prediction rates closer to 100% and false positive and false negative rates closer to 0%. Since the overall graduation rate is below 50%, the first blocks (Block 0s) of each model predicts all cases as non-events. Each Block 0 for each of the six models built has perfect sensitivity, specificity, and false negative rates.

The ROC curves for Block 2 of each of the six models discussed above are plotted in Figure 2 and the area under each of these ROC curves is described in Table 37. As both of these summaries show, each model predicts graduation at a comparable rate as the others; the 6-Year Component Model had the largest area under the curve value of .642 while each of the three composite models tied for the smallest area under the curve value of .636. The 6-Year Component Model had the greatest separation from the 'chance prediction' rate of .500.

Chapter V: Discussion

The current study was conducted to describe and evaluate the use of ACT-related scores to predict graduation from the University of Wisconsin-Stout within four to six years of matriculating. This study was not intended to evaluate the admissions criteria and does not make recommendations regarding these criteria.

Group Differences

The ANOVA comparing genders revealed that females performed significantly better on high school and college metrics (percentile rank, first and least GPA, and time to completion) and males performed significantly better on ACT metrics (ACT Math, Science, and Composite). These findings are consistent with Mau and Lynn (2001) and Struik and Flexer (1984) who found that males scored significantly higher ACT Composite scores while females earned significantly higher college GPA (see also Halpern, 2004). A possible explanation for this finding is research on stereotype threat. It could be that the ACT testing situation imposes additional cognitive strain on women which in turn affected their performance (O'Brien & Crandall, 2003). Pettijohn (1995) reported males earning higher ACT Composite scores and females earning higher high school and college GPA, although these differences were not significant. These findings lead to Mau and Lynn to assert "the more assessments are based on cognitive tests, the greater the male advantage, while the more assessments are based on coursework, the greater the female advantage" (2001, p135-136). Another possible explanation for this finding is that these gender differences may be influenced by cognitive factors such as item context (Gallagher, Levin, & Cahalan, 2002).

With the exception of one variable, the ANOVA comparing graduates and non-graduates confirms what one would expect: graduates perform significantly better than non-graduates.

Graduates had significantly higher percentile ranking, scored significantly higher on the ACT Math test, and higher first and last college GPA; non-graduates, however, scored significantly higher on the ACT Reading test. This suggests that the ACT test scores are not as meaningful when it comes to differentiating graduates from non-graduates (a hypothesis which is examined further below). However, this finding is tempered by the fact that in our data set, students who chose to transfer to a different university is also classified as “non-graduate” thus confounding the variable.

Logistic Regression

The primary objective of the current study was to determine the ability of ACT scores to predict graduation within a specified timeframe from the University of Wisconsin, Stout. These scores were tested in the presence of high school percentile ranking (a function of high school graduating class size and ordinal rank). Using only these variables, the model with the greater ability to predict graduation was the 6-Year Component Model. While this model resulted in fairly meager R^2 statistics relative to other disciplines (.060 and .080 for Cox & Snell R^2 and Nagelkerke R^2 , respectively), the model performed significantly better than predicting graduation based on chance alone ($\chi^2 = 193.8911, p < .001$). While the variables included in this model do not appear to share an appreciable amount of variance, one must consider the model is predicting an event six years in the future using only a measure of high school performance and scores on a standardized test.

Limitations

While several of the statistical procedures conducted in the current study resulted in a statistically significant finding, the practical significance of these differences and associations may be called into question. Cohen (1992, p. 156) explains the relationship between the sample

size (N), the effect size (ES), the level of accepted error (α), and the power of a statistical test: “ N increases with an increase in the power desired, a decrease in the ES, and a decrease in α .” The current study has a relatively large sample size ($N = 6,414$) and a typical acceptable error rate ($\alpha = 0.05$); the effect size was unknown. Given this, it is not surprising that several statistically significant findings were identified.

High school GPA would have been beneficial to include when building the six logistic regression models, however, this data was not available. As a result, percentile rank was used as the primary high school performance metric. While it has been previously shown that high school ordinal ranking was significantly related to high school GPA (Hamilton, 1990), extrapolating this relationship to high school percentile ranking may have overestimated the strength of the actual relationship between these variables.

References

- ACT. (1997). *ACT Assessment Technical Manual*. Iowa City, IA: Author.
- ACT. (2003a). *Preparing for the ACT Assessment: 2003-2004* (Publication No. IC 080192030).
Iowa City, IA: Author.
- ACT. (2003b). *User Handbook: 2003-2004* (Publication No. IC 070017030). Iowa City, IA:
Author.
- Alderman, D. L., & Powers, D. E. (1980). The effects of special preparation on SAT-Verbal scores. *American Educational Research Journal*, 17, 239-251.
- Anastasi, A. (1981). Coaching, test sophistication, and developed abilities. *American Psychologist*, 36, 1086-1093.
- Briggs, C. A. (2001). The effect of admissions test preparation: Evidence from NELS: 88. *Change*, 17, 10-18.
- Brigham, C. C. (1923). *A Study of American Intelligence*. NJ: Princeton University Press.
- Cohen, J. (1992). A power primer. *Psychological Bulletin*, 112, 155-159.
- Cronbach, L. J. (1990). *Essentials of psychological testing*, 5th Ed. NY: Harper & Row.
- Gallagher, A., Levin, J., & Cahalan, C. (2002). *Cognitive patterns of gender differences on mathematics admissions tests*. ETS Research Report 02-19.
- Goodwin, C. J., (1999). *A History of Modern Psychology*. NY: Wiley.
- Harvard. (2004). *History of the President's Office*. Accessed October 23, 2004 from
<http://www.president.harvard.edu/history/>
- Halpern, D. F. (2004). A Cognitive-process taxonomy for sex differences in cognitive abilities. *Currend Directions in Psychological Science*, 13, 135-139.
- Lemann, N. (1999, September 6). Behind the SAT. *Newsweek*, 134, 52-57.

- Mau, W. C., & Lynn, R. (2001). Gender differences on the Scholastic Aptitude Test, the American College Test and college grades. *Educational Psychology, 21*, 133-136.
- Murphy, K. R., & Davidshofer, C. O. (2001). *Psychological Testing Principles and Applications, 5th Ed.* Upper Saddle River, NJ: Prentice Hall.
- Nunally, J. C., & Bernstein, I. H. (1994). *Psychometric Theory, 3rd Ed.* NY: McGraw-Hill.
- O'Brien, L. T., & Crandall, C. S. (2003). Stereotype threat and arousal: Effects on women's math performance. *Personality and Social Psychology Bulletin, 29*, 782-789.
- PBS. (1999). *Frontline: Secrets of the SAT*. Accessed October 17, 2004, from <http://www.pbs.org/wgbh/pages/frontline/shows/sats/>
- Peng, C. Y., Lee, K. L., & Ingersoll, G. M. (2002). An introduction to logistic regression analysis and reporting. *Journal of Educational Research, 96*, 3-14.
- Pettijohn, T. F., II. (1995). Correlations among college students' grades point averages and American College Test scores. *Psychological Reports, 76*, 336-338.
- Powers, D. E. (1993). Coaching for the SAT: A summary of the summaries and an update. *Educational Measurement: Issues and Practice, 12*, 24-30, 39.
- Powers, D. E., & Rock, D. A. (1999). Effects of coaching on SAT I: Reasoning test scores. *Journal of Educational Measurement, 36*, 93-118.
- Rutherglen, S. (2000). The Scantron Aristocracy: Does the SAT measure merit? Does merit matter? [Review of the book *The big test*], *The Yale Review of Books, 3*(2). Retrieved October 19, 2004, from <http://www.yale.edu/yrb/summer00/review8.htm>
- Sawyer, R., Laing, J., & Houston, M. (1988). *Accuracy of Self-Reported High School Courses and Grades of College-Bound Students* (ACT Research Report No. 88-1). Retrieved January 14, 2004 from http://www.act.org/research/reports/pdf/ACT_RR88-1.pdf

- Struik, R. R., & Flexer, R. J. (1984). Sex differences in mathematical achievement: Adding data to the debate. *International Journal of Women's Studies*, 7, 336-342.
- Télez, K. (2001). 'The Big Men': A journalist's look at the Scholastic Aptitude Test. *Journal of Curriculum Studies*, 33, 247-260.
- Walsh, W. B., & Betz, N. E. (2001). *Tests and Assessment*, 4th Ed. Upper Saddle River, NJ: Prentice Hall.
- Wuensch, K. L. (2004). *Binary Logistic Regression with SPSS®*. Retrieved July 26, 2004, from <http://core.ecu.edu/psyc/wuenschk/MV/multReg/Logistic-SPSS.doc>
- Yerkes, R. M. (1918). Psychology in relation to the war. *Psychological Review*, 25, 85-115.
- Yerkes, R. M. (1921). *Psychological examining in the United States army*. Washington, DC: Government Printing Office.
- Yoakum, C. S., & Yerkes, R. M. (1920). *Army mental tests*. New York: Holt.

Table 1: Enrollment and Graduation Year-Term Breakdown

Year-Term	Enrollments		Graduations		
	<i>N</i>	% of Total <i>N</i>	<i>n</i>	% of Total <i>n</i>	% of Total <i>N</i>
1994-Fall	1,075	16.76%	0	0.00%	0.00%
1995-Spring	71	1.11%	0	0.00%	0.00%
1995-Summer	0	0.00%	0	0.00%	0.00%
1995-Fall	1,143	17.82%	0	0.00%	0.00%
1996-Spring	124	1.93%	0	0.00%	0.00%
1996-Summer	0	0.00%	0	0.00%	0.00%
1996-Fall	1,286	20.05%	1	0.04%	0.02%
1997-Spring	56	0.87%	0	0.00%	0.00%
1997-Summer	0	0.00%	0	0.00%	0.00%
1997-Fall	1,249	19.47%	8	0.35%	0.12%
1998-Spring	63	0.98%	103	4.53%	1.61%
1998-Summer	0	0.00%	33	1.45%	0.51%
1998-Fall	1,347	21.00%	108	4.75%	1.68%
1999-Spring	N/A	N/A	242	10.65%	3.77%
1999-Summer	N/A	N/A	30	1.32%	0.47%
1999-Fall	N/A	N/A	156	6.87%	2.43%

Year-Term	Enrollments		Graduations		
	<i>N</i>	% of Total <i>N</i>	<i>n</i>	% of Total <i>n</i>	% of Total <i>N</i>
2000-Spring	N/A	N/A	313	13.78%	4.88%
2000-Summer	N/A	N/A	44	1.94%	0.69%
2000-Fall	N/A	N/A	208	9.15%	3.24%
2001-Spring	N/A	N/A	335	14.74%	5.22%
2001-Summer	N/A	N/A	63	2.77%	0.98%
2001-Fall	N/A	N/A	204	8.98%	3.18%
2002-Spring	N/A	N/A	355	15.63%	5.53%
2002-Summer	N/A	N/A	69	3.04%	1.08%
Total	6,414	100.00%	2,272	100.00%	35.42%

Table 2: Demographical Breakdown

Variable	Valid <i>N</i>	Mean	SD	Median	Min.	Max.	Range
Age (in years)	6,409	18.93	2.35	18	17	68	51
High School							
Class Size	6,115	225.40	153.74	198	2	766	764
Ordinal Rank	6,115	95.46	87.79	66	1	503	502
Percentile Rank	6,112	59.70	21.07	59.78	0.30	100.00	99.70
ACT Scores							
Reading Test	5,541	21.20	4.69	21	7	36	29
Science Test	5,543	21.76	3.59	22	10	36	26
Mathematics Test	5,539	20.82	3.79	20	10	36	26
English Test	5,546	20.04	4.01	20	7	36	29
Composite	5,959	20.89	3.30	21	11	34	23
College Variables							
First GPA	5,280	2.67	0.71	2.73	0.11	4.00	3.89
Last GPA	5,398	2.79	0.66	2.88	0.11	4.00	3.89
Time to graduate	2,272	4.12	0.67	4.00	2.00	7.50	5.50

Table 3: Means and Standard Deviations of, and Correlations Among High School Variables

High School Variable	Mean	SD	1	2	3
1) Class Size	225.40	153.74	(6,115)		
2) Ordinal Rank	95.46	87.79	.772**	(6,115)	
3) Percentile Rank	59.70	21.07	-.124**	-.614**	(6,112)

NOTE: *N*s reported in parentheses.

** $p \leq 0.01$ (two-tailed).

Table 4: Means and Standard Deviations of, and Correlations Among ACT Variables

ACT Variable	Mean	SD	1	2	3	4	5
1) Reading	21.20	4.69	(5,541)				
2) Science	21.76	3.59	.595**	(5,543)			
3) Mathematics	20.82	3.79	.364**	.568**	(5,539)		
4) English	20.04	4.01	.660**	.561**	.456**	(5,546)	
5) Composite	20.89	3.30	.832**	.827**	.719**	.833**	(5,959)

NOTE: *Ns* reported in parentheses.

** $p \leq 0.01$ (two-tailed).

Table 5: Cross-Tabulation of Time to Graduation and Cohort Year

Time (t) Since Matriculation (in years)	Year Cohort Matriculated					Grand Total	% of Sample	% of Graduates
	1994	1995	1996	1997	1998			
$2 \leq t < 3^a$	2	4	0	3	6	15	0.23%	0.66%
$3 \leq t < 4$	142	144	199	172	203	860	13.41%	37.85%
$4 \leq t < 5$	235	248	342	311	N/A	1,136	17.71%	50.00%
$5 \leq t < 6$	69	58	89	N/A	N/A	216	3.37%	9.51%
$6 \leq t < 7$	24	19	N/A	N/A	N/A	43	0.67%	1.89%
$7 \leq t < 8$	2	N/A	N/A	N/A	N/A	2	0.03%	0.09%
Graduated Total	474	473	630	486	209	2,272	35.42%	100.00%
Not Graduated	672	794	712	826	1,138	4,142	64.58%	
Grand Total	1,146	1,267	1,342	1,312	1,347	6,414	100.00%	

^a These are graduates likely transferred, however, this information was not available.

Table 6: Means and Standard Deviations of, and Correlations Among College Variables

College Variable	Mean	SD	1	2	3
1) First GPA	2.6711	0.7107	(5,280)		
2) Last GPA	2.7920	0.6630	.862**	(5,398)	
3) Time to Degree	4.1163	0.6739	-.332**	-.328**	(2,272)

NOTE: *N*s reported in parentheses.

** $p \leq 0.01$ (two-tailed).

Table 7: High School Variables correlated with ACT Variables

ACT Variable	High School Variable		
	Class Size	Ordinal Rank	Percentile Rank
Reading Test	.006	-.057**	.151**
Science Test	.022	-.074**	.196**
Mathematics Test	-.005	-.177**	.347**
English Test	-.021	-.128**	.230**
Composite Score	-.001	-.131**	.279**

NOTE: $N = 5,435$.

** $p \leq 0.01$ (two-tailed).

Table 8: Gender Differences-Descriptive Statistics

Variable	N	Mean	SD	Std. Error	95% CI		Min	Max
					Lower	Upper		
<u>HS Class Size</u>								
Female	3,002	226.56	160.128	2.923	220.83	232.30	2	766
Male	3,113	224.27	147.331	2.641	219.09	229.45	2	762
<u>HS % Rank</u>								
Female	3,002	63.73	19.95	0.364	63.01	64.44	2.86	100.00
Male	3,113	55.76	21.44	0.384	55.00	56.51	0.00	100.00
<u>ACT Reading</u>								
Female	2,745	21.22	4.703	0.090	21.04	21.39	8	36
Male	2,796	21.17	4.670	0.088	21.00	21.35	7	36
<u>ACT Science</u>								
Female	2,747	20.93	3.283	0.063	20.81	21.05	10	36
Male	2,796	22.58	3.685	0.070	22.45	22.72	11	36
<u>ACT Math</u>								
Female	2,745	19.91	3.571	0.068	19.78	20.05	10	35
Male	2,794	21.72	3.785	0.072	21.58	21.86	10	36
<u>ACT English</u>								

Variable	N	Mean	SD	Std. Error	95% CI		Min	Max
					Lower	Upper		
Female	2,748	20.34	3.987	0.076	20.19	20.49	8	36
Male	2,798	19.75	4.018	0.076	19.60	19.90	7	36
<u>ACT Composite</u>								
Female	2,915	20.58	3.227	0.060	20.47	20.70	11	34
Male	3,044	21.17	3.342	0.061	21.06	21.29	11	33
<u>First GPA</u>								
Female	2,577	2.82	0.663	0.013	2.80	2.85	.11	4.0
Male	2,703	2.53	0.724	0.014	2.50	2.55	.12	4.0
<u>Last GPA</u>								
Female	2,636	2.94	0.605	0.012	2.92	2.97	.11	4.0
Male	2,762	2.65	0.683	0.013	2.62	2.67	.13	4.0
<u>Time to graduate (in years)</u>								
Female	1,261	3.99	0.621	0.017	3.96	4.02	2.5	6.8
Male	1,011	4.27	0.704	0.022	4.23	4.32	2.0	7.5

Table 9: Gender Differences-Analysis of Variance

Variable	Sum of Squares	df	Mean Square	F	Sig.
<hr/> HS Class Size <hr/>					
Between Groups	8052.410	1	8052.410	0.341	.559
Within Groups	144498986.710	6,113	23637.982		
<hr/> HS % Rank <hr/>					
Between Groups	97071.349	1	97071.349	226.003	< .001
Within Groups	2625617.821	6,113	429.514		
<hr/> ACT Reading <hr/>					
Between Groups	2.555	1	2.555	0.116	.733
Within Groups	121647.988	5,539	21.962		
<hr/> ACT Science <hr/>					
Between Groups	3795.498	1	3795.498	311.386	< .001
Within Groups	67539.432	5,541	12.189		
<hr/> ACT Math <hr/>					
Between Groups	4504.152	1	4504.152	332.504	< .001
Within Groups	75005.166	5,537	13.546		
<hr/> ACT English <hr/>					
Between Groups	479.816	1	479.816	29.951	< .001

Variable	Sum of Squares	df	Mean Square	F	Sig.
Within Groups	88816.361	5,544	16.020		
<u>ACT Composite</u>					
Between Groups	522.328	1	522.328	48.369	< .001
Within Groups	64327.930	5,957	10.799		
<u>First GPA</u>					
Between Groups	117.791	1	117.791	243.904	< .001
Within Groups	2548.955	5,278	0.483		
<u>Last GPA</u>					
Between Groups	117.221	1	117.221	280.494	< .001
Within Groups	2255.048	5,396	0.418		
<u>Time to graduate (in years)</u>					
Between Groups	45.147	1	45.147	103.906	< .001
Within Groups	986.306	2,270	0.434		

Table 10: Graduate/Non-Graduate Group Differences-Descriptive Statistics

Variable	N	Mean	SD	Std. Error	95% CI		Min	Max
					Lower	Upper		
<u>HS Class Size</u>								
Graduates	2,206	227.07	157.484	3.353	220.50	233.65	2	751
Non Graduates	3,909	224.45	151.595	2.425	219.70	229.20	2	766
<u>HS % Rank</u>								
Graduates	2,206	66.50	18.827	0.401	65.71	67.29	2.86	100.00
Non Graduates	3,909	55.82	21.343	0.341	55.15	56.49	0.00	100.00
<u>ACT Reading</u>								
Graduates	2,109	20.99	4.614	0.100	20.80	21.19	10	36
Non Graduates	3,432	21.32	4.726	0.081	21.16	21.48	7	36
<u>ACT Science</u>								
Graduates	2,110	21.71	3.589	0.078	21.56	21.87	11	36
Non Graduates	3,433	21.80	3.587	0.061	21.68	21.92	10	36
<u>ACT Math</u>								
Graduates	2,110	20.98	3.862	0.084	20.82	21.14	10	36
Non Graduates	3,429	20.73	3.741	0.064	20.60	20.85	10	34
<u>ACT English</u>								

Variable	N	Mean	SD	Std. Error	95% CI		Min	Max
					Lower	Upper		
Graduates	2,112	20.08	3.943	0.086	19.91	20.25	7	34
Non Graduates	3,434	20.02	4.056	0.069	19.89	20.16	8	36
<u>ACT Composite</u>								
Graduates	2,192	20.96	3.299	0.070	20.82	21.10	12	34
Non Graduates	3,767	20.84	3.299	0.054	20.73	20.95	11	32
<u>First GPA</u>								
Graduates	2,233	2.92	0.560	0.012	2.90	2.95	0.57	4.0
Non Graduates	3,047	2.49	0.751	0.014	2.46	2.51	0.11	4.0
<u>Last GPA</u>								
Graduates	2,270	3.12	0.405	0.009	3.11	3.14	1.9	4.0
Non Graduates	3,128	2.55	0.708	0.013	2.53	2.58	0.11	4.0

Table 11: Graduate/Non-Graduate Group Differences-Analysis of Variance

Variable	Sum of Squares	df	Mean Square	F	Sig.
<u>HS Class Size</u>					
Between Groups	9689.811	1	9689.811	0.410	.522
Within Groups	144497349.310	6,113	23637.715		
<u>HS % Rank</u>					
Between Groups	160902.783	1	160902.783	383.950	< .001
Within Groups	2561786.387	6,113	419.072		
<u>ACT Reading</u>					
Between Groups	140.870	1	140.870	6.422	.011
Within Groups	121509.673	5,539	21.937		
<u>ACT Science</u>					
Between Groups	9.084	1	9.084	0.706	.401
Within Groups	71325.845	5,541	12.872		
<u>ACT Math</u>					
Between Groups	83.650	1	83.650	5.832	.016
Within Groups	79425.668	5,537	14.345		
<u>ACT English</u>					
Between Groups	4.617	1	4.617	0.287	.592

Variable	Sum of Squares	df	Mean Square	F	Sig.
Within Groups	89291.560	5,544	16.106		
<u>ACT Composite</u>					
Between Groups	20.850	1	20.850	1.916	.166
Within Groups	64829.408	5,957	10.883		
<u>First GPA</u>					
Between Groups	246.122	1	246.122	536.651	< .001
Within Groups	2420.624	5,278	0.459		
<u>Last GPA</u>					
Between Groups	433.043	1	433.043	1204.966	< .001
Within Groups	1939.226	5,396	0.359		

Table 12: Predictor Analysis Results for 4-Year Component Model

Predictor	β	SE β	Wald's χ^2	df	p	Odds Ratio	95% CI	
							Lower	Upper
Block 0								
Constant	-0.4829	0.0279	300.1706	1	< 0.001			
Block 1								
Constant	-2.0001	0.1031	376.2193	1	< 0.001			
HS % Rank	0.0239	0.0015	242.3733	1	< 0.001	1.0242	1.0211	1.0273
Block 2								
Constant	-1.1717	0.1954	35.9535	1	< 0.001			
HS % Rank	0.0267	0.0017	245.3670	1	< 0.001	1.0271	1.0237	1.0305
ACT English	0.0038	0.0102	0.1379	1	0.710	1.0038	0.9839	1.0241
ACT Math	-0.0143	0.0098	2.1198	1	0.145	0.9858	0.9670	1.0050
ACT Reading	-0.0281	0.0088	10.2245	1	0.001	0.9723	0.9556	0.9892
ACT Science	-0.0089	0.0114	0.6014	1	0.438	0.9912	0.9692	1.0136

Table 13: Overall Model Evaluation for 4-Year Component Model

Overall Model Evaluation	χ^2	df	p
<hr/>			
Block 1			
<hr/>			
Step	259.3713	1	< .001
Block	259.3713	1	< .001
Model	259.3713	1	< .001
Block 2			
<hr/>			
Step	33.5357	4	< .001
Block	33.5357	4	< .001
Model	292.9071	5	< .001
<hr/>			

Note: Block 2 improvement over Block 1: $\chi^2(5, N = 5,454) = 6,992.4870 - 6,958.9512 = 33.5358, p < 0.0001$.

Table 14: Model Summary for 4-Year Component Model

Model Summaries	Result	<i>p</i>
Block 1		
Hosmer and Lameshow Test	$\chi^2 = 14.0912$.079
Cox & Snell	$R^2 = 0.0464$	
Nagelkerke	$R^2 = 0.0632$	
Block 2		
Hosmer and Lameshow Test	$\chi^2 = 12.8538$.117
Cox & Snell R^2	$R^2 = 0.0523$	
Nagelkerke R^2	$R^2 = 0.0711$	

NOTE: N = 5,454, df = 8.

Table 15: Classification Tables for 4-Year Component Model

Observed	Predicted		Correct
	Grad	Non-Grad	
Block 0			
Grad	0	2,081	0.00%
Non-Grad	0	3,373	100.00%
Correct	0.00%	61.84%	61.84%
Block 1			
Grad	456	1,625	21.91%
Non-Grad	418	2,955	87.61%
Correct	47.83%	64.52%	62.54%
Block 2			
Grad	458	1,623	22.01%
Non-Grad	409	2,964	87.87%
Correct	47.17%	64.62%	62.74%

NOTE: For all predictions, cut value = .5.

Table 16: Predictor Analysis Results for 4-Year Composite Model

Predictor	β	SE β	Wald's χ^2	df	<i>p</i>	Odds Ratio	95% CI	
							Lower	Upper
Block 0								
Constant	-0.5283	0.0271	379.6400	1	< .001			
Block 1								
Constant	-2.0627	0.0953	468.7742	1	< .001			
HS % Rank	0.0247	0.0014	295.6805	1	< .001	1.0251	1.0222	1.0279
Block 2								
Constant	-1.2376	0.1791	47.7626	1	< .001			
HS % Rank	0.0279	0.0016	312.5059	1	< .001	1.0283	1.0251	1.0315
ACT Composite	-0.0490	0.0091	29.1214	1	< .001	0.9522	0.9354	0.9693

Table 17: Overall Model Evaluation for 4-Year Composite Model

Overall Model Evaluation	χ^2	df	<i>p</i>
<hr/>			
Block 1			
<hr/>			
Step	319.0791	1	< .001
Block	319.0791	1	< .001
Model	319.0791	1	< .001
Block 2			
<hr/>			
Step	29.4135	1	< .001
Block	29.4135	1	< .001
Model	348.4927	2	< .001
<hr/>			

Note: Block 2 improvement over Block 1: $\chi^2(2, N = 5,829) = 7,368.6153 - 7,339.2018 = 29.4135$, $p = < 0.0001$.

Table 18: Model Summary for 4-Year Composite Model

Model Summaries	Result	<i>p</i>
Block 1		
Hosmer and Lameshow Test	$\chi^2 = 8.5207$.384
Cox & Snell	$R^2 = 0.0533$	
Nagelkerke	$R^2 = 0.0727$	
Block 2		
Hosmer and Lameshow Test	$\chi^2 = 11.0692$.198
Cox & Snell R^2	$R^2 = 0.0580$	
Nagelkerke R^2	$R^2 = 0.0792$	

NOTE: N = 5,829, df = 8.

Table 19: Classification Tables for 4-Year Composite Model

Observed	Predicted		Correct
	Grad	Non-Grad	
Block 0			
Grad	0	2,162	0.00%
Non-Grad	0	3,667	100.00%
Correct	0.00%	62.91%	62.91%
Block 1			
Grad	456	1,685	21.30%
Non-Grad	430	3,237	88.27%
Correct	51.47%	65.77%	63.58%
Block 2			
Grad	472	1,690	21.83%
Non-Grad	435	3,232	88.14%
Correct	52.04%	65.66%	63.54%

NOTE: For all predictions, cut value = .5.

Table 20: Predictor Analysis Results for 5-Year Component Model

Predictor	β	SE β	Wald's χ^2	df	<i>p</i>	Odds Ratio	95% CI	
							Lower	Upper
Block 0								
Constant	-0.2342	0.0308	57.6783	1	< .001			
Block 1								
Constant	-1.8193	0.1122	263.0437	1	< .001			
HS % Rank	0.0254	0.0017	221.2456	1	< .001	1.0257	1.0223	1.0291
Block 2								
Constant	-1.2110	0.2182	30.8171	1	< .001			
HS % Rank	0.0270	0.0019	208.8097	1	< .001	1.0274	1.0236	1.0311
ACT English	0.0003	0.0115	0.0006	1	0.980	1.0003	0.9781	1.0230
ACT Math	0.0024	0.0110	0.0471	1	0.828	1.0024	0.9809	1.0243
ACT Reading	-0.0355	0.0098	13.1011	1	< .001	0.9651	0.9468	0.9839
ACT Science	-0.0008	0.0127	0.0043	1	0.947	0.9992	0.9746	1.0244

Table 21: Overall Model Evaluation for 5-Year Component Model

Overall Model Evaluation	χ^2	df	<i>p</i>
<hr/>			
Block 1			
<hr/>			
Step	238.1714	1	< .001
Block	238.1714	1	< .001
Model	238.1714	1	< .001
<hr/>			
Block 2			
<hr/>			
Step	25.7292	4	< .001
Block	25.7292	4	< .001
Model	263.9006	5	< .001
<hr/>			

Note: Block 2 improvement over Block 1: $\chi^2(5, N = 4,263) = 5,613.5270 - 5,587.7978 = 25.7292, p = .0001.$

Table 22: Model Summary for 5-Year Component Model

Model Summaries	Result	<i>p</i>
Block 1		
Hosmer and Lameshow Test	$\chi^2 = 7.8883$.445
Cox & Snell	$R^2 = 0.0543$	
Nagelkerke	$R^2 = 0.0728$	
Block 2		
Hosmer and Lameshow Test	$\chi^2 = 7.8262$.451
Cox & Snell R^2	$R^2 = 0.0600$	
Nagelkerke R^2	$R^2 = 0.0804$	

NOTE: N = 5,004, df = 8.

Table 23: Classification Tables for 5-Year Component Model

Observed	Predicted		Correct
	Grad	Non-Grad	
Block 0			
Grad	0	1,883	0.00%
Non-Grad	0	2,380	100.00%
Correct	0.00%	55.83%	55.83%
Block 1			
Grad	456	1,097	29.36%
Non-Grad	611	1,769	74.33%
Correct	42.74%	61.72%	56.57%
Block 2			
Grad	848	1,035	45.03%
Non-Grad	609	1,771	74.41%
Correct	58.20%	63.11%	61.44%

NOTE: For all predictions, cut value = .5.

Table 24: Predictor Analysis Results for 5-Year Composite Model

Predictor	β	SE β	Wald's χ^2	df	p	Odds Ratio	95% CI	
							Lower	Upper
Block 0								
Constant	-0.2797	0.0300	87.1117	1	< .001			
Block 1								
Constant	-1.8526	0.1038	318.3637	1	< .001			
HS % Rank	0.0257	0.0016	258.2660	1	< .001	1.0261	1.0228	1.0293
Block 2								
Constant	-1.1385	0.1998	32.4616	1	< .001			
HS % Rank	0.0283	0.0017	266.0653	1	< .001	1.0287	1.0252	1.0322
ACT Composite	-0.0419	0.0101	17.2385	1	< .001	0.9589	0.9402	0.9781

Table 25: Overall Model Evaluation for 5-Year Composite Model

Overall Model Evaluation	χ^2	df	<i>p</i>
<hr/>			
Block 1			
<hr/>			
Step	279.8238	1	< .001
Block	279.8238	1	< .001
Model	279.8238	1	< .001
<hr/>			
Block 2			
<hr/>			
Step	17.3496	1	< .001
Block	17.3496	1	< .001
Model	297.1734	2	< .001
<hr/>			

Note: Block 2 improvement over Block 1: $\chi^2(2, N = 4,541) = 5,927.3731 - 5,910.0236 = 17.3495, p = .0002.$

Table 26: Model Summary for 5-Year Composite Model

Model Summaries	Result	<i>p</i>
Block 1		
Hosmer and Lameshow Test	$\chi^2 = 7.6916$.464
Cox & Snell	$R^2 = 0.0598$	
Nagelkerke	$R^2 = 0.0802$	
Block 2		
Hosmer and Lameshow Test	$\chi^2 = 7.5362$.480
Cox & Snell R^2	$R^2 = 0.0633$	
Nagelkerke R^2	$R^2 = 0.0850$	

NOTE: N = 5,004, df = 8.

Table 27: Classification Tables for 5-Year Composite Model

Observed	Predicted		Correct
	Grad	Non-Grad	
Block 0			
Grad	0	1,955	0.00%
Non-Grad	0	2,586	100.00%
Correct	0.00%	56.95%	56.95%
Block 1			
Grad	456	1,167	28.10%
Non-Grad	613	1,973	76.30%
Correct	42.66%	62.83%	57.71%
Block 2			
Grad	829	1,126	42.40%
Non-Grad	628	1,958	75.72%
Correct	56.90%	63.49%	61.37%

NOTE: For all predictions, cut value = .5.

Table 28: Predictor Analysis Results for 6-Year Component Model

Predictor	β	SE β	Wald's χ^2	df	<i>p</i>	Odds Ratio	95% CI	
							Lower	Upper
Block 0								
Constant	-0.1700	0.0359	22.4180	1	< .001			
Block 1								
Constant	-1.7304	0.1292	179.3135	1	< .001			
HS % Rank	0.0251	0.0020	161.0753	1	< .001	1.0255	1.0215	1.0295
Block 2								
Constant	-1.2754	0.2542	25.1732	1	< .001			
HS % Rank	0.0260	0.0022	144.0434	1	< .001	1.0264	1.0220	1.0307
ACT English	0.0013	0.0136	0.0085	1	0.926	1.0013	0.9749	1.0283
ACT Math	0.0126	0.0129	0.9523	1	0.329	1.0127	0.9874	1.0386
ACT Reading	-0.0403	0.0116	12.1382	1	.001	0.9605	0.9389	0.9825
ACT Science	0.0024	0.0149	0.0271	1	0.869	1.0025	0.9736	1.0321

Table 29: Overall Model Evaluation for 6-Year Component Model

Overall Model Evaluation	χ^2	df	<i>p</i>
<hr/>			
Block 1			
<hr/>			
Step	173.0401	1	< .001
Block	173.0401	1	< .001
Model	173.0401	1	< .001
<hr/>			
Block 2			
<hr/>			
Step	20.8509	4	< .001
Block	20.8509	4	< .001
Model	193.8911	5	< .001
<hr/>			

Note: Block 2 improvement over Block 1: $\chi^2(5, N = 3,125) = 4,136.6307 - 4,115.7798 = 20.8518, p = .0009$.

Table 30: Model Summary for 6-Year Component Model

Model Summaries	Result	<i>p</i>
Block 1		
Hosmer and Lameshow Test	$\chi^2 = 6.5162$	$= .590$
Cox & Snell	$R^2 = 0.0539$	
Nagelkerke	$R^2 = 0.0720$	
Block 2		
Hosmer and Lameshow Test	$\chi^2 = 7.5024$	$.484$
Cox & Snell R^2	$R^2 = 0.0602$	
Nagelkerke R^2	$R^2 = 0.0804$	

NOTE: N = 3,699, df = 8.

Table 31: Classification Tables for 6-Year Component Model

Observed	Predicted		Correct
	Grad	Non-Grad	
Block 0			
Grad	0	1,430	0.00%
Non-Grad	0	1,695	100.00%
Correct	0.00%	54.24%	54.24%
Block 1			
Grad	456	762	37.44%
Non-Grad	496	1,199	70.74%
Correct	47.90%	61.14%	56.81%
Block 2			
Grad	714	716	49.93%
Non-Grad	493	1,202	70.91%
Correct	59.15%	62.67%	61.31%

NOTE: For all predictions, cut value = .5.

Table 32: Predictor Analysis Results for 6-Year Composite Model

Predictor	β	SE β	Wald's χ^2	df	<i>p</i>	Odds Ratio	95% CI	
							Lower	Upper
Block 0								
Constant	-0.2130	0.0348	37.4230	1	< .001			
Block 1								
Constant	-1.7419	0.1191	213.9057	1	< .001			
HS % Rank	0.0252	0.0019	184.8534	1	< .001	1.0255	1.0218	1.0292
Block 2								
Constant	-1.1319	0.2318	23.8376	1	< .001			
HS % Rank	0.0273	0.0020	186.9207	1	< .001	1.0277	1.0237	1.0317
ACT Composite	-0.0359	0.0118	9.2956	1	.002	0.9648	0.9428	0.9873

Table 33: Overall Model Evaluation for 6-Year Composite Model

Overall Model Evaluation	χ^2	df	<i>p</i>
Block 1			
Step	199.5956	1	< .001
Block	199.5956	1	< .001
Model	199.5956	1	< .001
Block 2			
Step	9.3316	1	.002
Block	9.3316	1	.002
Model	208.9272	2	< .001

Note: Block 2 improvement over Block 1: $\chi^2(2, N = 3,336) = 4,387.4468 - 4,378.1152 = 9.3316, p = .0094$.

Table 34: Model Summary for 6-Year Composite Model

Model Summaries	Result	<i>p</i>
Block 1		
Hosmer and Lameshow Test	$\chi^2 = 6.1132$.635
Cox & Snell	$R^2 = 0.0581$	
Nagelkerke	$R^2 = 0.0777$	
Block 2		
Hosmer and Lameshow Test	$\chi^2 = 8.9116$.350
Cox & Snell R^2	$R^2 = 0.0607$	
Nagelkerke R^2	$R^2 = 0.0813$	

NOTE: N = 3,699, df = 8.

Table 35: Classification Tables for 6-Year Composite Model

Observed	Predicted		Correct
	Grad	Non-Grad	
<hr/> Block 0 <hr/>			
Grad	0	1,491	0.00%
Non-Grad	0	1,845	100.00%
Correct	0.00%	55.31%	55.31%
<hr/> Block 1 <hr/>			
Grad	456	822	35.68%
Non-Grad	493	1,352	73.28%
Correct	48.05%	62.19%	57.89%
<hr/> Block 2 <hr/>			
Grad	696	795	46.68%
Non-Grad	517	1,328	71.98%
Correct	57.38%	62.55%	60.67%

NOTE: For all predictions, cut value = .5.

Table 36: Comparison of Classification Tables

Model	Sensitivity	Specificity	False Positive	False Negative	Overall
4-Year Component					
Block 0	0.00%	100.00%	0.00%	38.16%	61.84%
Block 1	21.91%	87.61%	47.83%	35.48%	62.54%
Block 2	22.01%	87.87%	47.17%	35.38%	62.74%
4-Year Composite					
Block 0	0.00%	100.00%	0.00%	37.09%	62.91%
Block 1	21.30%	88.27%	48.53%	34.23%	63.58%
Block 2	21.83%	88.14%	47.96%	34.34%	63.54%
5-Year Component					
Block 0	0.00%	100.00%	0.00%	44.17%	55.83%
Block 1	29.36%	74.33%	57.26%	38.28%	56.57%
Block 2	45.03%	74.41%	41.80%	36.89%	61.44%
5-Year Composite					
Block 0	0.00%	100.00%	0.00%	43.05%	56.95%
Block 1	28.10%	76.30%	57.34%	37.17%	57.71%
Block 2	42.40%	75.72%	43.10%	36.51%	61.37%

Model	Sensitivity	Specificity	False Positive	False Negative	Overall
6-Year Component					
Block 0	0.00%	100.00%	0.00%	45.76%	54.24%
Block 1	37.44%	70.74%	52.10%	38.86%	56.81%
Block 2	49.93%	70.91%	40.85%	37.33%	61.31%
6-Year Composite					
Block 0	0.00%	100.00%	0.00%	44.69%	55.31%
Block 1	35.68%	73.28%	51.95%	37.81%	57.89%
Block 2	46.68%	71.98%	42.62%	37.45%	60.67%

Table 37: Area under the curve for Block 2 of each Model

Model	Area Under the Curve	Std. Error ^a	Asymptotic Sig. ^b	Asymptotic 95% CI	
				Lower	Upper
4-Year					
Component	.638	0.010	< .001	.619	.657
Composite	.636	0.010	< .001	.617	.655
5-year					
Component	.641	0.010	< .001	.622	.660
Composite	.636	0.010	< .001	.617	.656
6-Year					
Component	.642	0.010	< .001	.623	.661
Composite	.636	0.010	< .001	.617	.656

^a Under the nonparametric assumption

^b Null hypothesis: true area = .5

Figure 1: Time to Graduation (Population)

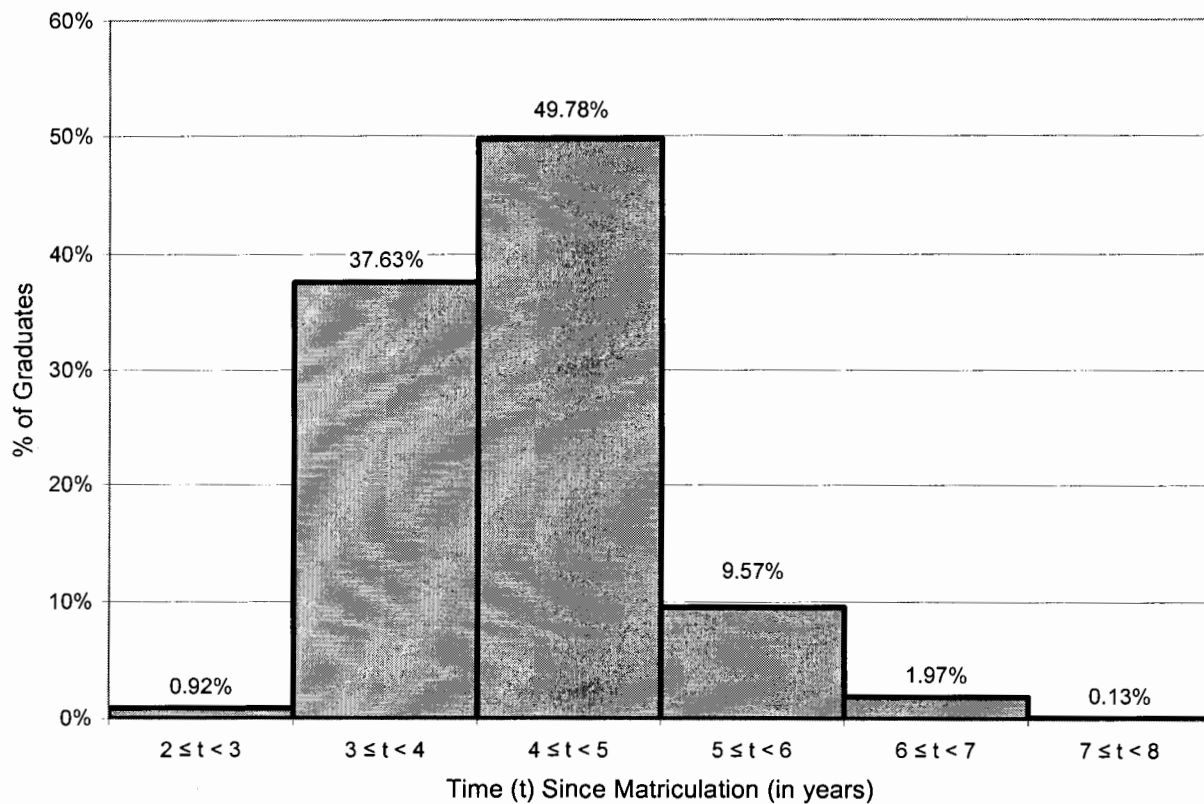


Figure 2: ROC Curves for all models

