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The use of merit-index measures to predict between-year retention of undergraduate college students

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**The use of merit-index measures to predict
between-year retention of undergraduate college students**

by

Robert Dean Reason

**A dissertation submitted to the graduate faculty
In partial fulfillment of the requirements for the degree of
DOCTOR OF PHILOSOPHY**

Major: Education (Higher Education)

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2001

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For the Major Program

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Chapter 1: Overview of Study

In one of the seminal studies of student retention, Astin (1975) concluded,

The most 'dropout-prone' freshmen are those with poor academic records in high school, low aspirations, poor study habits, relatively uneducated parents, and small town backgrounds. Dropping out is also associated with being older than most freshmen, having Protestant parents, having no current religious preference, and being a cigarette smoker. (p. 45)

Although likely antiquated and simplistic, this conclusion exemplifies the attempts of higher education researchers to identify specific student characteristics in the pursuit of a complete model to predict retention rates.

A quarter century later, higher education researchers are still attempting to identify concrete and specific characteristics that predict the likelihood a student will be retained to graduation (e.g., Murtaugh, Burns, & Schuster, 1999; Peltier, Laden, & Matranga, 1999). In fact, according to Roach (1999), interest in retention issues in higher education has reached an "all-time high" (p. 28). Attempts to understand, and thus improve, retention have ramifications for higher education budgets and services (Parker, 1999), issues of diversity (St. John, Hu, Simmons, & Musoba, 2001), and public perceptions of institutional success (Astin, Korn, & Green, 1987). All stakeholders of an institution must be concerned with the retention of its students (Parker).

The importance of understanding, predicting, and increasing retention rates should not be understated. Students, parents, and legislators use retention rates to compare colleges for quality and make decisions related to attendance and funding (Astin, 1997). Through these comparisons students are tacitly encouraged to avoid schools with low retention rates and enroll in schools with higher rates, as the latter are considered more successful institutions. In an era of accountability, where success is rewarded, budgetary allocations can

be linked to high retention rates (Moxley, 1999). In the higher education marketplace for students and money, retention is one measure of success.

From an institutional standpoint, “the success of an institution and the success of its students are inseparable” (Levitz, Noel, & Richter, 1999, p. 31). Retention rates become a key indicator of institutional success. Thus, while retention “is not the primary goal [of an institution]...it is the best indicator of student satisfaction and success” (p. 31). A greater understanding of what affects retention must improve the odds for student retention, and thus, institutional success.

Purpose of Study

The purpose of this study is twofold. First, using variables known to predict retention, this study attempts to determine, through logistic regression analysis, a model that includes only significant predictor variables and is fitted to the dataset under consideration. Second, the study compares the predictive power of two merit index measures (Cooper, 1999) with the more traditional predictor, ACT Composite score. One measure, the ACT-index, is based on the American College Testing (ACT) Composite Score. The second merit index measure is the SAT-index as defined by St. John and his colleagues (2001).

Importance of the Study

This study adds to the existing research base regarding retention by reevaluating several variables known to predict retention. This study also seeks to test, through replication, the findings of St. John and his colleagues (2001) related to the predictive power of merit-index scores, using a larger, more geographically broad sample than the St. John study. The merit-index holds theoretical advantages related to recruitment and retention of students (Roach, 1999; St. John et al., 2001), but confirmation of its predictive power

remains limited. Finally, this study adds an examination of the ACT Assessment, and a merit-index based on the ACT, to the retention literature base.

Questions and Hypotheses

To achieve the purposes of this study, four research questions guide the inquiry. Furthermore, three hypotheses were formulated.

Research Questions

1. Based on the results of backward stepwise regression model analyses, what model best fits the data examined?
2. Does the ACT-index score, formulated to consider the level of achievement of a student in relation to his or her peers, predict between-year retention as well as the more traditional ACT Composite score?
3. Does the ACT-index score predict between-year retention as well as the SAT-index, as defined by St. John and others (2001)?
4. Do differences exist between the three scores (ACT, ACT-index, and SAT-index) for the different racial categories in the sample?

Hypotheses

To achieve the stated purposes, the following null hypotheses will be tested:

1. There is no statistically significant difference between the fit of a retention model using ACT-index and a model using the ACT Composite score.

2. There is no statistically significant difference between fit of a retention model using SAT-index and a model using the ACT Composite score.
3. There is no statistically significant difference between the predictive power of a retention model that uses the ACT-index score and one that uses the SAT-index score.

Definition of Terms

The following terms and constructs require definition:

ACT Composite Score

The ACT composite Score is the average score an individual received on the four sections of the ACT Assessment (ACT, 2001b). Students take the ACT assessment prior to attending college, often in their junior or senior year of high school. Scores on the ACT Assessment range from 1 to 36.

ACT-Index Score

Adapted from the work of St. John et al. (2001) and Cooper (1999), the ACT-index score (ACT-index) is a merit index measure. For the purposes of this inquiry, the ACT-index is an individual's ACT composite score converted to a percentage of the average ACT composite score of his or her graduating class (ACTAVE). Specifically, the formula to derive ACT-index is $ACT \div ACTAVE \times 100$. A student scoring above the average for his or her class will have an ACT-index score greater than 100. A student scoring below the average will have an ACT-index score of less than 100.

Age

The age of each student was calculated as of September 1, 1999, the first semester of his or her first year of college.

Carnegie Classification

Institutions of higher education attended by the students in the sample were coded based on the 2000 Carnegie Foundation classification system (“Carnegie Classification Database,” 2000).

First-year College GPA

This variable reports the grade point average each student achieved during his or her first year of college, which consisted of the fall semester 1999 and spring semester 2000. First-year college GPA was reported to ACT, Inc. by each student’s higher education institution.

Estimated High School Rank

Students were asked to estimate their class rank in high school. Choices included top quarter, second quarter, third quarter, and fourth quarter. This variable was a self-reported estimate made by the students completing the ACT assessment and was not confirmed by either ACT or the students’ high schools.

First-year student

A first-year student is any first-time, full-time student in the first or second semester of college. All students in the sample under consideration were first-year students in the fall of 1999.

Gender

Gender is defined by ACT, Inc. as male or female. Although sex would be a more descriptive term, based on the dichotomous nature of this variable, in order to remain congruent with ACT, Inc. and other literature related to retention, the term gender will be used.

High School GPA

This variable was computed by ACT, Inc. from students' self-reported grades in 30 high school courses.

Persistence

Persistence is a measure of individual performance toward achieving an academic goal (Levitz et al., 1999). In contrast, retention is a measure of institutional success in keeping students enrolled in the institution. Although the two terms are inextricably interrelated, this study addresses the institutional measure of retention and, wherever possible, the individual construct of persistence is not used.

Race/Ethnicity

When completing ACT assessments, students were asked to indicate their race or ethnicity from one of eight choices, which were collapsed into five categories for this inquiry. The five racial/ethnic categories include Caucasian, African-American, Mexican-American/Hispanic, Asian-American/Pacific Islander, and multiracial/other. The multiracial/other category includes those respondents who selected multiracial, Native American/American Indian, or other non-Hispanic on the ACT assessment.

Retention

For the purposes of this study, retention is defined as reenrollment in the same college or university for a second consecutive year. The retention rate thus is an institutional measure of the percentage of first-year students who enroll for a second year at the same higher education institution. No distinction is made between "drop outs" and "stop outs" (Astin, 1975; Tinto, 1987).

SAT-Index Score

St. John et al. (2001) defined the SAT-index score as the difference between an individual student's SAT score and the average SAT score of all college-bound students in his or her high school. Because actual SAT scores were not reported for this sample, the SAT and average SAT scores used to determine SAT-index were derived using concordance tables that relate ACT to SAT (Astin, 1997; College Board, 2001; Sawyer & Brownstein, 1988).

Second-year student

A second-year student is any student who is in his or her third consecutive semester at the same college.

Delimitations

This study examines the relationship of several demographic variables (race, age, gender) and several cognitive variables (ACT Composite, high school and college grade point averages) to the first-to-second-year retention of college students who took the ACT Assessment and who are participating in the ACT Retention Study. This is a secondary analysis of existing data and, as such, some methodological limitations are present.

Several variables not included in the current study also have been found to be significant in predicting retention. Participation in first-year orientation programs (Murtaugh et al., 1999) and specifically designed intervention programs (Dale & Zych, 1996; Newman & Newman, 1999) affect retention. Non-cognitive variables related to desire to finish (Allen, 1999), satisfaction (Astin et al., 1987), social support (Gloria, Robinson Kupius, Hamilton, & Willson, 1999) and other personality characteristics (Tross, Harper, Osher, & Kneidinger, 2000) also affect retention of students. These variables are not included in the current study because they were not available through the ACT, Inc. database.

Finally, this study can make no conclusions regarding whether the decision to persist to the second year of college was the appropriate decision for an individual student. This study focuses on the institutional need to retain students. The underlying assumption of this inquiry is that retention is a positive characteristic for an institution and, thus, a high retention rate is desirable.

Chapter 2: Review of the Literature

Higher education research related to retention can be traced back over 70 years (Braxton, 2000) with much research pre-dating 1970 (e.g., Astin, 1964; Bayer, 1968; Vaughan, 1968). Two seminal works were published in 1975. Astin's (1975) book, entitled Preventing Students from Dropping Out, and Tinto's (1975) theory serve as foundational knowledge related to retention in higher education. Astin (1975) studied the effects of individual student characteristics, such as gender, age, and place of residency, and institutional characteristics, such as type, location, and selectivity, to determine how such variables affected student retention. Tinto (1975) posited a theory that incorporated a student's commitment to an institution, aspirations for a degree, and integration into the academic and social life of a campus. According to Tinto, high levels of integration into academic life of an institution led to a greater commitment to the institution (Braxton). A greater commitment and integration led to a greater likelihood that the student would be retained (Braxton; Braxton & Lien, 2000).

Research related to retention stalled, according to Braxton (2000), in the mid-1990s. Coupled with the rapidly changing demographics of college students (Keller, 2001; Pascarella & Terenzini, 1998), this suggests that the effects of several variables on student retention need to be reconsidered in contemporary higher education.

This chapter reviews relevant literature and research studies in three broadly defined areas, mainly focusing on research conducted during the 1990s and later to inform the direction of the study. First, the researcher examines studies related to the changing demographics of higher education. The changing demographics, it is believed, will affect how higher education researchers and policy makers view retention in the future. A thorough

understanding of the demographics of contemporary higher education is essential to formulating effective retention studies. Second, research specifically related to retention efforts is reviewed to inform the current study regarding significant variables identified in previous research. Finally, the last section of this chapter focuses on the merit-index score as a predictor of retention; specifically, the final section focuses on the study completed by St. John and colleagues (2001). Specific attention is paid St. John et al. because part of the current study replicates their procedures.

Demographic Studies

The traditional view of undergraduate college students as 18-22-year-old, white, full-time students attending residential colleges conforms to only a small part of contemporary college students (Keller, 2001; Pascarella & Terenzini, 1998; Woodard, Love, & Komives, 2000b). Many of the studies that make up the foundation of our knowledge about retention in higher education assumed the traditional view of students, rather than the reality of today's diverse student population (Pascarella & Terenzini). Thus, regardless of whether the older studies included representative samples of their contemporary higher education populations, it is likely those samples no longer represent the current higher education landscape.

Increasing Diversity of Undergraduate Students

Researchers (Keller, 2001; Pascarella & Terenzini, 1998; Woodard, Love, & Komives, 2000b) cite the increasing diversity of undergraduate college students in the United States. Most often cited is the increasing diversity among racial and ethnic identities of college students (Pascarella & Terenzini; Zusman, Fox, Gerth, & Coleman, 2000). The increasing number of women attending colleges and universities is well documented (Woodard et al.). The increasing diversity of age (Keller; Murdock & Nazrul Hoque, 1999)

and socioeconomic status (Murdock & Nazrul Hoque; Pascarella & Terenzini) deserve discussion as well. The following section discusses the growing diversity of undergraduate college students with regard to the categories cited.

People of Color

The racial and ethnic composition of undergraduate college students shifted dramatically in the last quarter century (Pascarella & Terenzini, 1998). Pascarella and Terenzini reported that between 1984 and 1994 the number of undergraduate students of color rose 61%, compared to a 5.1% increase in Caucasian students attending college. Students of color accounted for approximately one-fourth of the undergraduate population in 1994, up from one-fifth a decade earlier. Findings presented at the 2000 Association for the Study of Higher Education Conference confirmed these findings (Zusman et al., 2000).

Trends regarding the increasing racial and ethnic diversity within higher education will continue through the first decade of the 21st century (Keller, 2001; Woodard et al., 2000b; Zusman et al., 2000). States along the west coast and southwest of the United States expect a 40% increase in the number of undergraduate students attending college during that time period (Keller). Much of the increase in undergraduate students will be accounted for in new immigrants to the United States and domestic people of color, especially women of Hispanic origins (Zusman et al.).

Women

While increases in the number of students of color will account for the majority of the growth in higher education in the near future, the percentage of women attending institutions of higher education increased during the previous two decades and will continue to increase (Woodard et al., 2000b). In 1999, women accounted for 55% of the undergraduate population

in the United States, up from 50% in 1980. Rates of attendance for women at higher education institutions continue to grow faster than rates for men.

Other Changing Variables

Race, ethnicity, and gender are not the only measures of higher education student composition that are changing currently. Higher education also must be ready to serve students who are diverse in age and socioeconomic status (SES). The United States population continues to age and the rates at which older Americans return to college will continue to grow (Keller, 2001; Murdock & Nazrul Hoque, 1999). Moreover, races are aging in structurally different ways (Murdock & Nazrul Hoque). The average age of minorities will grow at faster rates than the average age for Caucasians. This likely will be reflected in the students served by higher education in the future.

Many of the demographic changes discussed thus far will impact the average SES of the United States' population and the college-aged population (Murdock & Nazrul Hoque, 1999). Experts predict that the average American household income will decrease in the future. Minorities and older people have, on average, lower incomes than Caucasians and younger people. This, along with shrinking public financial support of higher education (Pascarella & Terenzini, 1998), will affect how and when students are retained, stop out, or drop out of college. Future retention studies should include variables related to SES to examine the effects of these financial and demographic changes.

Implications for Research

The demographic changes within higher education will force researchers to change how and why research is conducted (Pascarella & Terenzini, 1998). In turn, rapid changes in research will influence the practice of student affairs. Woodard, Love, and Komives (2000a)

believe that student affairs professionals must be “scholar-practitioners” (p. 58), so that practice can remain current with research in the dynamic environment of higher education. The breadth and depth of knowledge necessary for informed practice in an era of rapid changes in the demographics of higher education will require more of both scholars and practitioners. Research, thus, must be dynamic, responsive to change, and useful to practitioners in higher education settings.

Higher education research, according to Pascarella and Terenzini (1998), must change. Finding inclusive and representative samples of highly diverse populations is and will continue to be very difficult, but essential to thorough research studies. Researchers must include variables related to sexual orientation, student status (full- or part-time), commuter status, and work/family responsibility, for example, along with the traditional age, gender, race, and ethnicity variables for samples to be truly representative of the current student population.

Further, Pascarella and Terenzini (1998) posited that the increased student diversity will impact higher education research in three ways. First, researchers must study the conditional, or interaction^d effects of demographic variables. Researchers must examine the interaction between variables (e.g., race and gender) to move our understanding of students further. Second, researchers must redefine college outcomes to match the students’ purposes of attending higher education institutions. Not all students enter institutions with the expressed desire to graduate with a degree. Graduation thus might be an inappropriate measure of a successful outcome for many students. Finally, researchers must set aside the traditional approaches to inquiry. Isolating a small number of variables to examine their impacts will no longer suffice. Studies must be inclusive of as many variables and

interactions as possible in order to fully understand retention issues in light of the increasingly diverse student population.

The current study addresses the first recommendation of Pascarella and Terenzini (1998). Traditional demographic variables are re-examined in the contemporary, highly diverse undergraduate population. Less traditional retention variables, the merit-index measures, for example, will be added to the more traditional demographic variables to increase our understanding of retention. Further, the merit-index measures account for the interaction of several demographic characteristics (Cooper, 1999; St. John et al., 2001) by attempting to mediate some of the differential in ACT composite score that might be accounted for by characteristics of the students' high school experiences. In theory, the merit-index measure removes some of the disparity between groups by giving credit to students who exceed the average score of their high school classmates (Cooper). Future studies must address the second and third recommendations made by Pascarella and Terenzini.

Retention Studies

The changing demographic characteristics of undergraduate students notwithstanding, higher education researchers and policy makers have a solid foundation of empirical research related to retention. Peltier et al. (1999), in a review of research related to retention, cited many student background variables that directly affect the probability that an institution will retain students. According to an analysis by Peltier and others, gender, race and ethnicity, SES, high school grade point average, college grade point average, as well as the interaction between these variables, were related to retention.

A review of literature by the researcher discovered similar trends in retention studies. Variables related to high school achievement and race/ethnicity were statistically significant in many retention studies reviewed (Peltier et al., 1999). Results related to the influence of gender on retention were mixed, although interactions between gender and race provided insight into retention. Finally, in studies that examined retention beyond the first semester of college, college grade point average was significantly related to retention.

For the sake of organization, the following review addresses major variables separately. This should not be interpreted, however, to mean these variables are independent of each other. On the contrary, the reviewed studies indicate that the following variables interact with each other. They are presented separately here only for explanation and ease of understanding.

High School Achievement Variables

Variables that indicate the level of achievement in high school—high school grade point average (HS GPA) and college admissions test scores (SAT/ACT)—appeared to consistently significantly predict retention (Astin et al., 1987; Tross et al., 2000). These variables were included in practically all retention studies and often were considered student background variables in models that included multiple other variables related to retention.

In an example of the predictive power of high school achievement variables, Astin and colleagues (1987) reported the results a follow-up study related to the Cooperative Institutional Research Program (CIRP) at the University of California-Los Angeles. Astin et al. surveyed approximately 8,000 students, matching CIRP follow-up data with student retention data from higher education institutions. The authors used three progressively more

stringent definitions of retention and conducted a series of regression analyses to identify the strongest predictors of retention.

The student's self-reported HS GPA and institution-reported SAT/ACT were "the two strongest predictors of retention" for each of the three definitions of retention (Astin et al., 1987, p. 39). Students entering college with an A average from high school, for example, were seven times more likely to graduate with a degree in four years than were students entering with a C average from high school. Further, students with the highest SAT scores were six times more likely to graduate in four years than were students with the lowest SAT scores. Although high school achievement measures statistically significantly predicted retention in this study, these measures accounted for only 12% of the variance in retention.

A recent study found a much higher level of variance accounted for by these two variables, 29% (Tross et al., 2000). Tross et al. studied the between-year retention of 844 first-year students at one Southeastern university. As part of a stepwise multiple regression analysis, college retention was regressed onto HS GPA, SAT/ACT, and three non-cognitive variables. Only HS GPA, SAT/ACT, and student conscientiousness remained significant predictors of retention in the final model, with HS GPA accounting for 25% and SAT/ACT accounting for 4% of the variance in retention as indicated by eta-squared statistics.

Similarly, Levitz et al. (1999) reported a linear relationship between SAT/ACT and retention. Institutions that report the highest averages of college entrance examination scores for their students had an average first-to-second-year retention rate of greater than 91%. Institutions reporting the lowest average scores for their students, or open-door institutions, had retention rates closer to 56%—an attrition rate five times worse.

These studies highlight the importance of HS GPA and SAT/ACT as predictor variables; although, researchers may underestimate the predictive power of either variable. Due to the high collinearity present between HS GPA and SAT/ACT (Wolfe & Johnson, 1995) some of the predictive power associated with the two variables is lost. Collinearity is the correlation between two or more predictor variables. If collinearity is high, “only some of the predictor variables will enter the ... analysis as predictors, even though all of them might predict the criterion variable to some extent” (Gall, Borg, & Gall, 1996, p. 438). Thus high collinearity can lead to underestimation of the predictive effects of variables.

Gender

Research results have been mixed regarding the influence of a student’s gender on retention. Astin (1977), Astin and others (1987), and Tinto (1987) found that gender was statistically significantly related to whether a student was retained. Peltier and others (1999) reported relatively consistent findings over time that gender was predictive of retention, with women more likely to be retained than men.

In a recent study (St. John et al., 2001), gender played a less important role. St. John and his colleagues examined three progressively more inclusive regression models. Gender was not significant in the model that included only variables related to gender, age, race, financial dependency on parents, family income, and SAT/Merit-Index. Gender became significant in model two, which added variables related to first-semester college GPA, but failed to remain significant when institutional variables were added.

Since the institutional variables related to type of institution, degree program, and housing type were statistically significantly related to retention, and gender failed to achieve significance when these variables were added, the authors concluded that some interaction

occurred among the variables, stating that “males have some advantage compared to females because of the type of college attended or the increased probability of living on campus. Clearly, gender differences in persistence is a topic that merits further investigation” (St John et al., 2001, p. 144).

The type of interaction found by St. John and his colleagues (2001) is similar to the findings of other studies. Murtaugh and others (1999) found relationships between gender and race that influenced retention. These findings support the assertion by Pascarella and Terenzini (1998) that the interaction effects of variables have increased in importance as the diversity within higher education grows.

Race and Ethnicity

Race and ethnicity are prevalent in the literature related to retention (Peltier et al., 1999). In many places throughout the literature race and ethnicity were conflated into one variable. Although this is not ideal, to avoid confusion and remain congruent with the literature, the term race will be used in this review to encompass both constructs.

Race has been found to be a significant predictor of the retention of undergraduate students (Astin, 1997; Murtaugh et al., 1999; Peltier et al., 1999). Further, studies conclude that different variables significantly predict retention for different racial groups (Allen, 1999; Hall, 1999). Various racial groups likely have different experiences related to education, which affect how variables affect their retention rates. Therefore, race is both a predictor and a mediator of other variables related to retention.

Race

A review of the literature related to race and retention revealed statistically significant relationships consistently throughout several decades of study (Peltier et al., 1999). In more

recent studies of retention, however, the impact of race has been less consistent, especially in multivariate models (Murtaugh et al., 1999; St. John et al., 2001). Practical and statistical differences do remain, however, in the retention rates of racially diverse students. Recent studies, for example, reveal that Asian American and/or Caucasian students were most likely to be retained in college, while other racial groups were less likely to be retained (Astin, 1997; Murtaugh et al.; Peltier et al.).

Murtaugh et al. (1999), in a study of almost 9,000 students at Oregon State University in the early 1990s, used stepwise univariate and multiple regression analysis to create hazard ratios for several racial categories. Hazard ratios were defined as “factors by which a student’s hazard of withdrawal is multiplied by a unit increase in the predictor” (p. 361). Setting the retention rate of white students equal to one allowed the researchers to compare retention across racial categories.

In a univariate model, only Asian American students in the Murtaugh et al. (1999) study achieved a hazard ratio less than one, meaning that Asian American students were less likely than white students to drop out of college. African American, Hispanic, American Indian, and Pacific Islander students had hazard ratios greater than one, with African American, Hispanic, and American Indian hazard ratios statistically significantly greater. Students from these racial groups were more likely than white students to withdraw from the university.

The effects of race were mitigated when other demographic variables were included in the analysis (Murtaugh et al., 1999). When age, country of residence (domestic or international student), college major, high school GPA, first-quarter college GPA, and participation in a freshman orientation class were considered, much of the difference between

racial groups disappeared or reversed. The difference between Asian American and white students remained relatively constant, although this relationship became statistically significant in the multivariate analysis. The hazard ratio for African American students remained statistically significant but moved below one. This result meant that African American students, holding all other variables constant, were more likely to be retained than white students. No other statistically significant hazard ratios were found.

Different Experiences

The experiences of students of color on predominantly white campuses are different from the experiences of white students (Gloria et al., 1999). Therefore, excluding variables from an equation and examining race independently of them is a statistical manipulation that bears little resemblance to reality. Allen (1999) found that different variables were significant in predicting the retention of minority students than were significant in predicting the retention of white students. In a study of 581 first-year students at one university in the Southwest United States, Allen found that the student's high school rank, first-year college GPA, and a self-reported measure of desire to finish college accounted for 68% of the variance in the retention of minority students' from the first to second year of college. For non-minority students, however, high school rank, first-year college GPA, and parental education were significant, accounting for 38% of the variance in retention.

Hall (1999) also reported differences in predictor variables of retention from the first to second year of college for minority and non-minority students. Studying 368 African American students and 1,880 white students at St. John's University, Hall found that first-semester college GPA and a desire to live near home predicted retention for both groups. The two groups had no other significant predictor variables in common. For white students, high

school achievement variables (defined above), self-concept related to academics, and financial aid in the form of grants also predicted retention. For the African American students, the opportunity to get a job to assist with expenses and a belief that their college should prohibit racist/sexist speech predicted retention.

Summary

While race is a significant predictor, studies also indicate that different racial groups have different variables that affect retention. The findings support the assertion by Pascarella and Terenzini (1998) that researchers should examine the differential effects related to race and ethnicity in higher education research. Through the years the effects of race on retention have changed. While a study of retention should include race as a variable, the statistical analysis must be sophisticated enough to examine the interactions of race with other variables. It is likely, as studies suggest (Allen, 1999; Hall, 1999), that the experiences of students of color are different enough from the experiences of white students that the two should be examined separately.

First-year College GPA

Given the disproportionate number of students who leave college between the first and second year of college, this time period appears to be an appropriate focus for retention studies (Levitz et al., 1999). Tinto (1996) reported that approximately 57% of college dropouts leave before the start of the second year. Interventions to increase retention often focus on first-year students (Davidson & Muse, 1994; Murtaugh et al., 1999), because “the greatest attrition tends to occur between the freshman and sophomore years” (Murtaugh et al., p. 356).

Intervening to retain students past the first year is the “most efficient way to boost graduation rates” (Levitz et al., 1999, p. 37). Attrition rates reduce by half for each year past the first that an institution can retain a student. According to Levitz et al., if an institution’s first-to-second-year attrition rate is 30%, it is likely the second-to-third year attrition rate will be 15%, and approximately 7.5% the subsequent year. Reducing the initial rate, then, likely reduces the subsequent rates proportionally, and impacts greatly an institution’s average retention rate over four years.

When studying retention of college students past the first semester of college, researchers are able to examine the influence of predictor variables related to students’ college experiences on the models. An examination, then, of between-year retention, specifically retention from the first to second year of college, allows for a model that includes variables related to initial college experiences. Studies that examine within-year retention, that is retention from the first to second semester (e.g., St. John et al., 2001), may limit artificially the influence of college experiences.

First-year college GPA, a measure of initial academic success, has been found to be a statistically significant predictor of retention in several studies (Allen, 1999; Mitchel, Goldman, & Smith; 1999; Murtaugh et al., 1999). Recall that Allen found that first-year college GPA was a statistically significant predictor of between-year retention for both minority and non-minority students in the study. For both minority and non-minority students, college GPA exerted the largest direct effect on whether a student was retained.

In the analysis reported by Murtaugh et al. (1999), first-quarter GPA was used to predict retention between the first and second years of college. The probability of returning for a second year of college increased dramatically with higher GPAs. Students with the

lowest GPA (0.0 – 2.0) had a 57% probability of being retained, while students with the highest GPAs (3.3 – 4.0) had a 91% probability of being retained. Further, in a multivariate model, Murtaugh et al. reported that the value of the hazard ratio for GPA was .49.

Therefore, for each point increase in GPA the probability of withdrawal from the university decreases by 49%.

Summary

Astin (1997) indicated that four variables “account[ed] for the bulk of variance in retention” (p. 649). Those four variables included high school grades, admissions test scores (ACT or SAT), gender of the student, and race of the student. Over time these four variables consistently have been found to be significant (Peltier et al., 1999), although the relationships have changed. A reexamination of the effects of these variables on the retention of contemporary college students is essential to understanding retention. A comprehensive examination of retention rates, thus, should include these four variables.

Studies also indicated that student attrition is most likely to occur between the first and second year of college (Davidson & Muse, 1994; Murtaugh et al., 1999). Empirical studies that examine significant variables related to between-year retention specific to the first-to-second-year transition should be of particular interest to higher education researchers and policy makers. Further, when considering retention between the first and second year of college, student achievement in college, as measured by first-semester grade point average, proves to be a significant variable in retention.

The current inquiry includes those variables identified as relevant by previous research: high school GPA, ACT Composite score, gender, and race of the student. Based on

more recent research, described below, another measure of high school achievement—the merit-index score—is considered in the current research.

The Merit-Index Score

In an attempt to increase the diversity within higher education, as well as to counter attacks on affirmative action policies, researchers and policy experts proposed the use of the merit-index as an admission criterion (Cooper, 1999; St. John et al., 2001). The merit-index quantifies the relationship between a student’s score on an admissions exam, such as the American College Test (ACT) or the Scholastic Aptitude Test (SAT), and the average score for all college-bound students within the same school during the same test administration period. According to Goggin (as cited in Cooper), this merit-index score “gives students credit for exceeding the average [score] of their high school classmates” (p. 35). The merit-index score differentiates students from their peers who, presumably, have similar high school experiences, especially related to environmental factors that affect learning.

St. John and his colleagues (2001), in a study of 2,500 students at several Indiana colleges and universities, assigned each student a merit-index score that was the difference between his or her SAT score and the average SAT score of his or her graduation class. The study then compared the predictive value of the merit-index score to the predictive value of the raw SAT score for within-year retention. Logistic regression models were estimated using several traditional demographic variables with the merit-index, then again with the same demographic variables but with the raw SAT Composite scores. The authors compared the results of the two regression equations.

The authors (St. John et al., 2001) found that a student’s merit-index score had similar predictive capabilities for within-year persistence as did the student’s SAT score. In a

logistic regression analysis, a 100-point increase in raw SAT score resulted in a corresponding 1.8% increase in the probability that a student would persist between the first and second semester ($p < .001$). Similarly, a 100-point increase in the merit-index score resulted in a 1.6% increase in the probability of student persistence ($p < .001$). Merit-index thus was equally predictive of within year persistence as was the more traditional measure, SAT Composite score.

According to St. John and colleagues (2001), the results hold practical significance for the recruitment and retention of a diverse undergraduate student population. The merit-index score provides an equally predictive alternative measure upon which to recruit students whom the institution has an acceptable probability of retaining. Students who score equally better than their classmates, for example 20 points higher than the class average, seem to be equally likely to persist whether the students come from a lower-scoring, inner-city school or a higher-scoring, suburban school.

The study by St. John and his colleagues (2001) provides a framework by which to further examine the merit-index score. The current research uses similar statistical methods to examine the data. Similar findings are expected.

Conclusion

The literature reviewed in this chapter supports two major points. First, continued study of retention is important. The rapidly changing demographics of the undergraduate student population leave our understanding of variables affecting retention in need of updating. As an increasing number of students from formerly underrepresented groups come to campus, the effects of race, gender, ethnicity, age, and other demographic variables will change. New studies must reexamine our understanding of these variables and their

relationship to retention. Sophisticated studies must examine the interaction of these variables to understand fully the differential experiences of various populations.

Second, the literature review identifies several traditionally studied variables for inclusion in the current retention study and one new variable. Variables such as high school grade point average (HS GPA), college entrance examination scores (SAT/ACT), socioeconomic status (SES), race/ethnicity, and gender should be included as predictor variables in all retention studies. The newly identified variable, merit-index score, shows promise to serve as a significant predictor of retention as well (St. John et al., 2001). The efficacy of the merit-index score should continue to be studied as an alternative to, and in addition to, the traditional predictor variables.

Chapter 3: Methodology

This study regressed the dependent variable, retention, on several independent predictor variables. A backward stepwise regression procedure was used to determine the model that most efficiently predicted student retention. Independent predictor variables included sex, age, and race of the student; high school GPA; high school rank; standardized test scores; and Carnegie classification of the student's higher education institution. These variables had been determined to be predictive in previous retention studies (Astin, 1997; Astin et al., 1987; Levitz et al., 1999; Murtaugh et al., 1999; Peltier et al., 1999; Tross et al., 2000).

Three logistic regression analyses were conducted. First, the researcher estimated a regression model using the above independent variables and each student's composite ACT score. This traditional examination served as a baseline model. The ACT-index variable then was introduced as a substitute for the ACT composite score and the backward stepwise regression procedure was repeated to determine the predictive power of the ACT-index. Finally, the SAT-index variable was included in place of the ACT-index. Comparisons of the three models, using chi-square goodness-of-fit and pseudo- R^2 techniques, were made to determine if the models that employed the merit-index variables were equally predictive as the model using the ACT composite variable.

This chapter describes the data source, population and sample, and the analysis of the data. The advantages of using logistic regression with dichotomous dependent variables are delineated. A detailed discussion of the interpretation that accompanies logistic regression is also provided.

Data

This study used secondary data collected by and obtained from the American College Testing Program (ACT) in Iowa City, Iowa. ACT, Inc. offers a wide range of services to secondary schools, colleges, universities, and other educational agencies (ACT, 2001a). The data come from three sources: the 1998 - 1999 administration of the ACT Assessment, the dependent variable came from the ACT Retention Survey, and average ACT scores were derived from ACT, Inc. market research.

Sample

The sample for this study consisted of 87,915 students who sat for the ACT Assessment during the 1998-1999 administration and who, in the fall of 1999, enrolled as first-time, first-year students at 4-year institutions of higher education that participated in an on-going retention study with ACT, Inc. during the 1999-2000 academic years. Of the 87,915 in the original sample, 10,103 (11.5%) were removed following a missing data analysis, leaving 77,812 usable cases in the sample. The demographic characteristics of the sample, contained in Tables 1 through 3, indicated a broadly representative sample.

A frequency analysis of the dependent variable, retention, revealed that of the 77,812 students in the sample, 58,352 (74.8%) were retained and 19,608 (25.2%) were not retained for a second year. A random sample of 19,608 retained students was selected in order to evenly distribute the dependent variable. The even distribution of cases among the dependent variable is important to correctly gauging the strength of the logistic equations. Logistic regression analysis attempts to classify cases into the dichotomous groups of the dependent variable. One way we understand the ability of a logistic regression model is to examine the percentage of cases the model correctly classifies (Mertler & Vannatta, 2001; Shelley, 1999).

Table 1. Frequencies for Categorical Variables in Original Sample

Category	Frequency	Valid Percentage
Gender		
Male	34,053	43.8%
Female	43,759	56.2%
Total	77,812	100.0%
Race/Ethnicity		
Caucasian	61,906	83.3%
African-American	5,585	7.5%
Mexican-American/Hispanic	3,651	4.9%
Asian-American/ Pacific Islander	1,414	1.9%
Multiracial/Other	1,797	2.4%
Total	74,353	100.0%
Estimated High School Ranking		
Top Quarter	39,279	53.6%
Second Quarter	24,838	33.9%
Third Quarter	8,318	11.4%
Fourth Quarter	813	1.1%
Total	73,248	100.0%
Carnegie Classification		
Doctoral Extensive	30,909	39.6%
Doctoral Intensive	6,784	8.7%
Master's I	33,316	42.7%
Master's II	1,169	1.5%
Bachelor's/Liberal Arts	1,031	1.3%
Bachelor's/General	4,752	6.1%
Total	77,961	100.0%

Table 2. Means and Standard Deviations of Continuous Variables in Original Sample

Category	Mean	Standard Deviation	Frequencies
ACT Composite Score	22.28	4.23	77,961
English ACT Score	22.03	4.98	77,961
Math ACT Score	21.78	4.69	77,961
Reading ACT Score	22.67	5.58	77,961
Science ACT Score	22.11	4.20	77,961
High School GPA	3.33	0.53	72,927
College GPA	2.60	0.96	76,059
Age	18.07	0.54	77,737

With a disparate representation of retained and non-retained students in the sample, the procedure is likely to correctly classify the retained students at an inflated rate. The over-classification of retained students, in turn, will inflate the overall percentage of correctly classified cases and overstate the predictive power of the model. An equal representation of retained and non-retained students in the final sample alleviates these concerns.

Table 3. Frequencies of Retained Students in Original Sample

	Frequency	Valid Percentage
Retained	58,352	74.8%
Not Retained	19,608	25.2%
Total	77,960	100.0%

Finally, cases with fewer than 10 ACT tests were deleted from the sample to alleviate the influence of one student's ACT composite score on the ACT average for his or her class. Since the ACT-index is the ACT composite divided by ACT average (times 100), removing cases with less than 10 scores factored into the denominator lessened the impact of any one score affecting the ACT-index. Only 427 cases were removed from the sample in this procedure.

The final sample, therefore, contained 38,789 cases approximately equally distributed between retained ($n = 19,422$; 50.1%) and non-retained ($n = 19,367$; 49.9%) students. Frequencies of demographic variables of the final sample are presented in Chapter 4.

Variables

The variables included in this study were selected to reexamine and improve upon existing retention studies, and to examine the efficacy of the ACT-index and SAT-index scores as predictors of retention with the fitted model. The variables selected for this study were based on the extensive literature base reviewed and summarized in Chapter 2. The dependent variable for all analyses was the dichotomous variable retention, which has been coded 0 or 1 to indicate whether a student returned for the second consecutive year of college (0 = not retained; 1 = retained).

Independent variables related directly to each student included sex, age as of September 1, 1999, race, self-reported high school class ranking (RANK), high school grade point average (HS GPA), and ACT composite score (ACT). A computed variable, ACT-index score (ACTINDEX), is the ratio of ACT to the average ACT score of a student's graduating high school class. To compute the SAT-index score, ACT scores are first

converted to SAT-equivalent scores. SAT scores are then subtracted from the average SAT-equivalent score for the students' high school classes. This procedure is congruent with St. John et al.'s (2001) procedure. Finally, the variable Carnegie classification (CARN) indicates the type of higher education institution each student attended in the fall of 1999.

Statistical Analysis

Descriptive and inferential statistics were used to examine the differences and to make inferences in this quantitative research design. Logistic regression analysis was the primary statistical procedure. A backward stepwise logistic procedure was utilized to construct the most predictive model from the available data. Goodness-of-fit and psuedo-R² tests were examined to determine differences between the resulting models.

Logistic Regression Analysis

Using logistic regression, the researcher regressed the dichotomous response variable, retention, on a series of predictor variables. Logistic regression is a non-linear regression analysis used when the response variable is categorical and dichotomous (Agresti, 1990, 1996; Freund & Wilson, 1997; Neter, Kutner, Nachtsheim, & Wasserman, 1996; Shelley, 1999). Further, the independent variables must be in the form of continuous or dummy variables (Sweet, 2000). In the case of this retention study, the response variable is coded 0 = "no, the student was not retained" and 1 = "yes, the student was retained." The categorical independent variables (e.g., sex or race) were dummy coded.

As with any regression analysis, logistic regression fits a response function to a model that relates independent variables to a response variable (Agresti, 1991, 1996; Blose, 1999).

In linear regression that model takes the form:

$$Y_i = \beta_0 + \beta_1 X_i + \epsilon_i.$$

In logistic regression the general model assumes the form:

$$Y_i = E(Y_i) + \varepsilon_i$$

where $E(Y_i)$, the expected value of Y at $x = i$, is the probability that $Y = 1$ at $x = i$. By extension, a similar model for multiple independent variables is possible. The resulting fitted multiple regression model then becomes:

$$E(Y) = \beta_0 + \beta_1 X_{i1} \dots \beta_{p-1} X_{i,p-1} \text{ (Shelley, 1999),}$$

where β_1 refers to the effect of X_1 on the log odds of success, controlling for the other values of X (Agresti, 1996).

The “effects in the logistic model refer to odds, and the estimated odds at one value of x divided by the estimated odds at another value of x is an odds ratio” (Agresti, 1990, p. 86).

The response function for the logistic regression model is the logarithm of the ratio of success to failure, the log odds, and is written as,

$$\text{Log} (\pi(x) / 1 - \pi(x)),$$

where $\pi(x)$ is the probability of success ($Y = 1$) and $1 - \pi(x)$ is the probability of failure ($Y = 0$) at a given level of X (Agresti, 1990, 1996).

In the fitted logistic regression model, then, the parameter estimates (β) are interpreted as the estimated odds of $Y = 1$ at $X = i$. Based on the algebra of the response function, β can be interpreted to approximate the odds increase, e^β , for each unit increase in X . For example, the value of β associated with GPA would indicate the extent to which the odds of retaining a student increase (assuming a positive β), measured as e^β , for each one-point increase in GPA.

Appropriateness of Logistic Regression to Retention Data. Logistic regression analysis has been used to study the retention of college students consistently (Dey & Astin, 1993). In a comparison of three methods—logistic, probit, and linear regression—applied to the same retention data, Dey and Astin found little difference in the results offered by each model. Although practical advantages to logistic regression were not found, theoretical advantages remain. Logistic regression analysis is “based on different assumptions than those used by linear models, and as such are theoretically more appropriate for studying dichotomous phenomena such as retention issues” (p. 572).

Many of the assumptions of the more common linear regression models are violated when the response variable is dichotomous (Shelley, 1999). Linear regression is based on the assumption that the error terms of the model are normally, independently distributed with a mean equal to 0 and a constant variance (Neter et al., 1996). Error terms in the regression model with a binary response variable cannot be normally distributed because there are only two possible error values (Shelley). Further, the variances of the error terms are dependent on the X variable and are thus not constant. The violation of these assumptions makes the application of linear regression to a dichotomous response variable, like retention, tenuous.

One theoretical advantage of logistic over linear regression is the sigmoidal, S-shaped, response function (Neter et al., 1996; Shelley, 1999). Logistic regression estimates the probability of success in the response variable given the values of the independent variables. The response function of a regression on a dichotomous variable represents a series of probabilities, which are constrained to a range of 0 to 1. In this study, for example, we are asking the probability of retaining a student (success) given a series of demographic and

cognitive variables. The fitted response function will represent the probabilities of retaining students, given the students' combination of independent variables.

The sigmoidal shape of the response function accounts for the different probabilities of the response variable at various levels of independent variables (Dey & Astin, 1993). That is, the logistic regression function is steepest when the probability of $y = 1$ is 0.5. It flattens out as the probability of $y = 1$ nears the two poles, 0 or 1, becoming almost linear (Neter et al., 1996). Thus, "changes in independent variables have the largest effects when probability levels approach .5 (where the slope is steepest) and smaller effects as probability levels approach 0 and 1" (p. 572).

In this study, the response variable, Y , equals the number of students retained in a sample of \underline{n} students, then the sigmoidal shape of the response function mimics closely the relationship between the probability of achieving Y successes in \underline{n} trials. Charting the probability, from 0 to 1, on the Y -axis and number of trials, \underline{n} , on the X -axis shows this relationship. The response function is steepest at that \underline{n} at which the probability of achieving Y successes is .5, and flatter when the probability nears 0 or 1.

SPSS uses a maximum likelihood procedure to determine the beta coefficients for a logistic regression model (Green, Salkind, & Akey, 2000). In a logistic regression model, the beta coefficient, β , is the rate of change of the response function (Agresti, 1996). The sign of β indicates whether the function ascends or descends, that is whether the relationship between the probability of Y and the number of trials is positive or negative. As the probability of Y , for a given number of trials, approaches 1 or 0, the value of β for the response function approaches 0. If $\beta = 0$, the response function is horizontal and there is no relationship between the response variable and the predictor variable(s).

Summary. In general, logistic regression analysis “fits a curvilinear response function that relates one or more independent variables to a dichotomous response variable” (Blose, 1999, p. 78). In so doing, logistic regression permits the estimation of the probability of a successful outcome for every combination of the independent variables, based on the actual data. Logistic regression, therefore, will allow for the estimation of probable retention rates for each combination of independent variables based on the actual retention and characteristics of students in the sample.

Backward Stepwise Procedures

To create the most accurately predictive retention model, this study uses a backward stepwise multiple logistic regression procedure, which may identify the most important predictor variables for the data (Shelley, 1999). This backward elimination procedure begins with all identified predictor variables. Through a series of regression analyses, the least helpful predictor variable at each step in each regression model is eliminated. The variable with the largest, non-significant P-value when testing $H_0: \beta = 0$ is eliminated at each step (Agresti, 1996). When the backward progression is completed, only statistically significant variables remain in the model.

At each successive step, the changes in goodness-of-fit of the series of models should be examined to determine if the eliminated variable added significantly to the model. To test this, the chi-square value from the second model (M2 with df2 degrees of freedom) is subtracted from the chi-square value from the first model (M1 with df1). The difference, with M2df-M1df degrees of freedom, can be compared to a chi-square table to test for significance. If the associated p-value is greater than the established alpha level, the stepwise regression can continue (Agresti, 1996).

When comparing multiple logistic regression models, the difference in the amount of variance explained (R^2) for each model should be examined also. A pseudo- R^2 statistic examines the proportion of the error variance reduced in the alternative regression model compared to the error variance in the null model (St. John et al., 2001). The Cox and Snell pseudo- R^2 statistic compares the log-likelihood of the fitted model to the log-likelihood of the null model. The Nagelkerke pseudo- R^2 statistic divides the chi-square value for the alternative model by the chi-square value for the model testing the null hypothesis (Shelley, 1999). Although either pseudo- R^2 statistic may be used to examine the fitted model, in this study the Nagelkerke pseudo- R^2 was employed.

Interpretations of Logistic Regression Output

Mertler and Vannatta (2001) suggested that interpretation of logistic regression model output be divided into three sections: the statistics related to overall model fit, the classification table, and the summary of model variables. Statistics related to the overall fit of a logistic regression model include the -2 Log Likelihood statistic, the pseudo- R^2 statistics, and the model chi-square. The classification table compares predicted outcome to the actual values of the dependent variable and provides a percentage of correctly classified by the fitted model. The third component of interpreting logistic regression output, the summary of model variables, includes the beta coefficient and its associated Wald statistic and odds ratio. Each of these is explained below.

Overall Goodness-of-Fit Measures

Several statistical procedures are available to evaluate the fit of the fitted logistic regression models (Agresti, 1990, 1996; Green et al., 2000; Norusis, 1999; Shelley, 1999). For a more complete understanding of the goodness-of-fit for the logistic regression models

under consideration in this inquiry, multiple procedures will be employed. This section explains each goodness-of-fit measure in detail.

-2 Log Likelihood Test. To determine how well the overall model fits the data, the -2 log likelihood test (-2 log L) is completed (Agresti, 1990, 1996; Shelley, 1999; St. John et al., 2001). This procedure uses the maximum likelihood estimation method, which estimates the parameter value at which the probability of the observed value is greatest. For binary response variables, for example, the probability is generally maximized at y/N . That is, the maximum likelihood of achieving y successes out of N trials is greatest when the probability of y , $\pi(y)$, equals y divided by the number of trials (Agresti, 1996). The determination of maximum likelihood is computationally complex and often left to computer software.

The $-2 \log L$ statistic (G^2) then compares the maximized likelihood function for the full model, l_1 , to the maximized value of the model representing the null hypothesis, l_0 . (Agresti, 1996). The test statistic equals

$$G^2 = -2 \log L = -2 [\log (l_0) - \log (l_1)]$$

and is compared to a chi-square table to determine the level of significance (Agresti; Shelley, 1999). Generally, a lower value of G^2 indicates a better fit (Mertler & Vannatta, 2001; St. John et al., 2001).

Hosmer and Lemeshow Chi-Square. The Hosmer and Lemeshow (HL) Chi-Square test is another statistic used to indicate how well a model fits the data (Hosmer & Lemeshow, 1989; Norusis, 1999). The HL test assesses the difference between the observed and expected numbers of successes (retained) and failures (non-retained) for the data divided into ten approximately equal groups based on the estimated probability of the event occurring (Norusis). A chi-square value is calculated using the common formula,

$$\text{SUM} [(\text{observed count} - \text{expected count})^2 / \text{expected count}]$$

and compared against a chi-square table with eight degrees of freedom at an the established alpha level.

A significant chi-square test allows for the rejection of the null hypothesis that there is no difference between the observed and the predicted values (Norusis, 1999). A well-fitted model will not result in significant differences between observed and expected values in the dependent variable. Therefore, a well-fitted model will not reject the null hypothesis under the Hosmer and Lemeshow test.

Allison (1999) cautioned against “concluding that a model is OK just because the HL test is not significant” (p. 56). Following a series of simulations testing the HL statistic, Allison concluded that the HL statistic was not very powerful. Therefore, while the HL test will be used to understand the models produced in this study, it will not be used exclusively to exclude or include a model in the analysis. The HL test will be used as part of a battery of analyses to judge the power of all the models.

Nagelkerke R² statistic. The final measure of goodness-of-fit employed in this study is the Nagelkerke R² statistic, a pseudo R² statistic, which roughly estimates the amount of variation in the dependent variable explained by the model (Norusis, 1999). Shelley (1999) and Norusis (1999) both cautioned that a direct analogy with the R² statistics from ordinary least squares regression is not appropriate with pseudo R² statistics like Nagelkerke.

Classification Table

The second component of logistic regression output identified by Mertler and Vannatta (2001) was the classification table. The classification table is one way to examine model discrimination (Norusis, 1999), that is the ability of the fitted model to distinguish

between the two outcomes of the dependent variable. Further, the classification table allows for further understanding of how well the model fits the actual data.

Output for logistic regression analysis from SPSS™ includes a classification table that compares the predicted outcomes of the dependent variable to observed outcomes (Norusis, 1999). The classification table provides the number of cases correctly and incorrectly classified for each of the two outcomes of the dependent variable and the percent correctly classified for the overall model. Although no statistical measure of significance is provided, the classification table is a practical tool for gauging the strength of a model and differences between models, with a higher percentage of correctly classified cases indicating a better model fit.

Summary of Model Variables

The third component of interpreting logistic regression output is an examination of the model variables. The null hypothesis for any logistic regression model is $H_0: \beta = 0$ (Agresti, 1996). Under the null hypothesis, the probability of success is independent of the predictor variables. The null hypothesis is represented by a horizontal response function, where $\beta = 0$. Statistical procedures are available to determine if a parameter estimate for β significantly differs from 0. These statistical procedures test the model variables.

Wald Chi-Square. To determine the statistical significance of each parameter estimate in the model, the Wald chi-square test will be evaluated (Shelley, 1999). The Wald chi-square statistic is the square of the ratio of the parameter estimate divided by its standard error. Using a chi-square table and knowing the appropriate degrees of freedom, statistical significance can be determined. A statistically significant Wald chi-square statistic allows the researcher to reject the null hypothesis, $H_0: \beta = 0$, in favor of the alternative hypothesis, $H_A:$

$\beta \neq 0$. Rejecting the null hypothesis indicates that the independent variable associated with β significantly affects the dependent variable.

The Wald statistic is considered a very conservative statistic (Tabachnick & Fidell, 1996; Sweet, 2000). Because of its conservative nature, Sweet recommends applying a liberal alpha level (e.g., $p < .10$) when interpreting the significance of the Wald statistic. While sound advice, given the large number of cases in the sample for this study, the alpha level for Wald statistical procedures will be set at $p < .05$, a more traditional level for social sciences (Freund & Wilson, 1997).

Odds Ratio. Finally, the odds ratio, which was explained in the methodology section above, for each independent variable should be examined. The odds ratio is a measure of the influence on the dependent variable for each independent variable (Agresti, 1996). Since the sample in this study is rather large ($n = 39,216$), analysis of the Wald statistic is likely to produce many significant variables. Examination of the odds ratio, in tandem with the Wald statistic, will allow for a better understanding of the actual predictive power of each independent variable.

Limitations of the Study

This study is limited by the data available for examination. Several individual variables identified as significant by Tinto (1987) are not included in the current study, including a student's commitment to higher education or intention to graduate. Non-cognitive variables related to feelings of fit or belonging are also excluded from the study due to the lack of availability of such data.

Based on the available data, the research cannot determine the reason for non-retained students. This is a further limitation of the study. Students leave for various reasons (Astin,

1975, 1997; Tinto, 1987) and with different intentions of returning to the same or another higher education institution. Future studies should make distinctions between students who leave voluntarily or are expelled by the institution and students who intend to return or transfer from those who have no intention to continue in higher education. It is quite likely that the reasons students leave, and their intentions to return following their departure, will influence (or be influenced by) the variables that predict their retention.

Conclusion

This study uses a backward elimination process to find the multiple logistic regression model that is best fitted to the data. Using the best predictive model, the ACT composite score variable is replaced, in two separate analyses, with the computed merit-index scores—ACT Index and SAT Index. The predictive powers of the three models will be compared to determine if the use of the merit-index scores to replace ACT is advantageous to predicting retention of college students from the first and second year.

Chapter 4: Research Findings

Research findings from the current study are reported in this chapter. Findings for the study are outlined in the following sections: 1) Descriptive Statistics, 2) Results of Logistic Regression Analysis, and 3) Results by Racial Category.

Descriptive Statistics

One purpose of research is to describe the phenomenon under investigation (Gall et al., 1996). The descriptive statistics presented in this section attempt to describe both the characteristics of the sample and the relationship between variables under consideration. The descriptive statistics presented address measures of central tendency and variability in the sample demographics by presenting frequencies, means, and standard deviations. Correlational statistics also are presented to “describe in mathematical terms the strength of the relationship between...variables” (p. 180). This section is meant to provide the reader with a thorough understanding of the data under consideration before inferential statistics are presented.

Sample Demographics

The distribution of sample demographic variables ($n = 38,789$) is presented in this section. Frequencies and percentages of categorical variables, such as gender, race/ethnicity, estimated high school ranking, and Carnegie classification are presented in Table 4. Means and standard deviations of the continuous variables—ACT Composite and subsection scores, ACT index score, SAT index score, high school GPA, and age—are presented in Table 5. Finally, Table 6 presents the distribution of the dependent variable, retention.

Table 4. Sample Frequencies and Percentages for Categorical Variables

Category	Frequency	Valid Percentage
Gender		
Male	17,291	44.7%
Female	21,408	55.3%
Total	38,699	100.0%
Race/Ethnicity		
Caucasian	30,361	82.2%
African-American	2,940	8.0%
Mexican-American/Hispanic	1,973	5.3%
Asian-American/ Pacific Islander	686	1.9%
Multiracial/Other	958	2.6%
Total	36,918	100.0%
Estimated High School Ranking		
Top Quarter	17,908	49.2%
Second Quarter	13,181	36.2%
Third Quarter	4,819	13.2%
Fourth Quarter	507	1.4%
Total	36,415	100.0%
Carnegie Classification		
Doctoral Extensive	14,614	37.7%
Doctoral Intensive	3,491	9.0%
Master's I	17,362	44.8%
Master's II	593	1.5%
Bachelor's/Liberal Arts	425	1.1%
Bachelor's/General	2,304	5.9%
Total	38,789	100.0%

Gender

Female students ($n = 21,408$) constituted 55.3% of the sample. Male students ($n = 17,291$) constituted the remaining 44.7%. These percentages are approximately equivalent to the gender breakdown of the college student population in the United States (National Center for Education Statistics, 2001a, 2001b). The National Center for Education Statistics (NCES), for example, reported that female enrollment in college remained relatively stable, approximating 56%, from 1996 through 2000, the last year for which such numbers are available (NCES, 2001b).

Race/Ethnicity

Race and ethnicity, as stated previously, was conflated into five categories: Caucasian, African-American, Mexican-American/Chicano/Hispanic, Asian-American/Pacific Islander, and Multiracial/Other. Caucasian students ($n = 30,361$) made up 82.2% of the sample for this study. Approximately 8.0% of the sample reported being African-American ($n = 2,940$). Mexican-American/Chicano/Hispanic students ($n = 1,973$) and Asian-American/Pacific Islanders ($n = 686$) constituted approximately 5.3% and 1.9% of the sample, respectively. The category that included respondents indicating multiracial or “other” racial categories accounted for 2.6% of the sample ($n = 958$).

The sample for this study overrepresented Caucasian and Hispanic students while underrepresenting African-American students. Nationally, only 71.8% of all students taking the ACT during the 1999 test administration period indicated Caucasian as their racial category (Texas Education Agency, 2000). Nationally, African-American students represented 10.2% and Mexican-American/Chicano/Hispanic students 5.2% of test takers in 1999. Data related to Asian-American/Pacific Islanders were not available for comparison.

Estimated High School Ranking

When asked to indicate their rank among their high school classmates, 49.2% (n = 17,908) of students in the sample indicated that they were in the “top quarter” of their high school class. Further, 36.2% (n = 13,181) indicated “second quarter” and 13.2% (n = 4,819) indicated “third quarter.” Only 1.4% (n = 507) of the sample indicated that they were in the bottom quarter of their high school class.

Carnegie Classification

Higher education institutions attended by the students in the sample were coded for Carnegie classification based on the classification system introduced by the Carnegie Foundation in August 2000 (“Carnegie Classification Database,” 2000). The sample consisted of 17,362 (44.8%) students attending Master’s I institutions and 14,614 (37.7%) students attending Doctoral Extensive institutions. Further, 3,591 (9.0%) students attended Doctoral Intensive and 2,304 (5.9%) students attended Bachelor’s/General institutions. Less than 2% of the sample attended either Master’s II institutions (n = 593; 1.5%) or Bachelor’s/Liberal Arts institutions (n = 425; 1.1%).

ACT Composite Score

The students in the sample achieved a mean ACT Composite score of 21.2 (SD = 4.24). The students in this sample appeared to have scored slightly better than the national average during the same time period. The national ACT composite mean for the 1999 assessment administration was 21.0 (Texas Education Agency, 2000). Mean sample scores for each of the ACT subsections also are reported in Table 5. These scores are not used in the data analysis, but are provided here for informational purposes.

Table 5. Sample Means and Standard Deviations for Continuous Variables

Category	Mean	Standard Deviation	Frequencies
ACT Composite Score	21.92	4.24	38,789
English ACT Score	21.63	5.00	38,789
Math ACT Score	21.36	4.65	38,789
Reading ACT Score	22.36	5.60	38,789
Science ACT Score	21.80	4.22	38,789
ACT Index	103.76	18.69	38,789
SAT Index	30.73	156.75	38,775
High School GPA	3.27	0.55	36,032
Age	18.08	0.56	38,685

ACT-Index

The mean ACT-index for the sample was 103.76 (SD = 18.69). Recall that the ACT-index measure is a student's ACT composite score expressed as a percentage of the average of his or her classmates. On average, therefore, students in the sample scored 104% of the average ACT score of their high school classmates who completed the ACT Assessment during the same administration period.

SAT-Index

The students in the sample achieved a mean SAT-index score of 30.73 (SD = 156.75). After converting the ACT composite and ACT average scores to SAT equivalents, the students in the sample, on average, scored 30.73 points above the average score of their high

school classmates. The standard deviation associated with SAT-index indicated a large range within the sample.

High School GPA

Students reported their grades for 30 high school courses. Each student's high school GPA was computed from grades reported for these 30 courses. The mean high school GPA for all students in the sample was 3.27 (SD = 0.55).

Age

The average age of the sample was 18.08 (SD = .56) years as of September 1, 1999. The sample ranged in age from 14 to 39 years.

Retention

As explained earlier, the researcher attempted to attain an equal representation of retained and non-retained students.

Table 6. Sample Frequencies and Percentages for the Dependent Variable—Retention—Following Random Selection of Retained Students

	Frequency	Valid Percentage
Retained	19,422	50.1%
Not Retained	19,367	49.9%
Total	38,789	100.0%

Correlation Matrix

Table 7 presents the correlation matrix for all variables under consideration in the inquiry. Researchers examine correlation coefficients of variables used in any form of regression analysis for high levels of correlation (Mertler & Vannatta, 2001), which indicates multicollinearity, a problem resulting “when [independent variables] are highly correlated ($r = .90$) with each other” (p. 342). Multicollinearity interferes with the ability to determine the amount of influence each independent variable exerts on the dependent variable (Freund & Wilson, 1997; Gall et al., 1996; Mertler & Vannatta).

Previous researchers (Wolfe & Johnson, 1995) cautioned against the inclusion in the same model of COLL GPA and assessment scores (ACT/SAT) because of high collinearity. Although the correlation between COLL GPA and other independent variables did not reach the $r = .90$ level suggested for exclusion by Mertler and Vannata (2001), high levels of collinearity with several independent variables, and the concerns expressed by Wolfe and Johnson, led to the removal of COLL GPA from the model. During initial regression analyses, high levels of collinearity with COLL GPA masked the effects of the high school achievement variables, HS GPA and ACT, ACT-index, or SAT-index.

Correlation coefficients between other independent variables did not reach levels that caused concern about collinearity.

Results of Logistic Regression Analyses

Several logistic regression analyses were conducted to determine which independent variables were predictors of between-year retention for college students in the sample. Initially, the three variables of interest (ACT, ACT-index, and SAT-index) were explored using simple logistic regression analysis. Results of these analyses are presented below.

Table 7. Correlation Coefficients for Independent Variables

	GEN	AGE	RACE	RANK	HS GPA	CARN	RETAIN	ACT AVE	ACT INDEX	SAT INDEX	ACT
GEN	1	-0.118	0.007	-0.065	0.132	0.021	0.031	-0.033	-0.032	-0.031	-0.045
AGE		1	0.019	0.103	-0.112	0.046	-0.037	-0.027	-0.131	-0.134	-0.132
RACE			1	0.071	-0.069	-0.036	-0.040	-0.256	-0.078	-0.087	-0.194
RANK				1	-0.672	0.022	-0.187	0.015	-0.448	-0.494	-0.449
HS GPA					1	-0.038	0.229	0.081	0.506	0.512	0.509
COLL GPA						-0.013	0.459	0.207	0.290	0.295	0.367
CARN						1	-0.048	-0.061	-0.073	-0.071	-0.093
RETAIN							1	0.138	0.130	0.996	0.187
ACTAVE								1	-0.093	-0.071	0.390
ACTINDEX									1	0.996	0.877
SATINDEX										1	0.890
ACT											1

Apparent differences in the predictive power of each independent variable indicated that further analysis, with more complex regression models, was appropriate.

Model 1 included the students' raw ACT Composite score (ACT). The second and third simple regression models replaced ACT with ACT-index (ACT-INDEX) and SAT-index (SAT-INDEX) scores, respectively. A constant-only regression model that included no independent variables served as a baseline for comparison. The results of each logistic regression analysis are presented in this section and in Table 8. Between-model comparisons based on goodness-of-fit statistics, percentage correctly classified, and the total variance explained by each model are also presented in this section.

Table 8. Simple Logistic Regression Model Statistics

Model	Model X^2	-2 log L	Goodness-of-Fit X^2	Nagelkerke R^2	% Correctly Classified
Constant-only		53,772.894			
ACT-only	1,371.991	52,400.903	8.215	0.046	57.7%
ACT-index	666.040	53,106.854	13.441	0.023	55.3%
SAT-Index	696.696	53,056.765	17.380 *	0.024	55.3%

* $p < .05$

Simple Regression Models

To determine a baseline understanding of the predictive nature of the ACT, ACT-index, and SAT-index variables, three simple logistic regression models were estimated. Significant results from these three models indicated that each variable was predictive of

retention and allowed for further inquiry with more complex regression models. This section explains the findings of the three logistic regression models individually. Table 9 presents the statistics related to the three independent variables.

Table 9. Simple Logistic Regression Independent Variables Statistics

Model	B	Standard Error	Wald	Odds Ratio
Constant-only	0.003	.010	0.078	1.003
ACT-only	0.091	.003	1,308.467 **	1.095
ACT-index	0.014	.001	649.224 **	1.014
SAT-Index	0.002	.000	678.295 **	1.002

*p < .05; **p < .001

Constant-Only Model

An initial logistic regression model that included only the constant, with no independent variables, was fitted for comparison purposes. The constant-only model served as the baseline model by which to judge the goodness-of-fit of models that included independent variables. An initial -2 Log L value of 53,772.894 was obtained from the constant-only model. Differences between this measure and the -2 Log L measures of the following simple logistic regression models are an indication of fit and can be used to compare models (Shelley, 1999).

ACT Composite Score

The dependent variable, retention, was regressed on ACT to determine if a statistically significant relationship existed. Logistic regression results indicated that ACT was statistically reliable in distinguishing between retained and non-retained students, although the model, with only one independent variable, was poorly fitted to the data (-2 Log L = 52,400.903; Model $\chi^2(1) = 1,371.991$, $p < .001$). A non-significant Hosmer and Lemeshow test ($\chi^2(8) = 8.215$, $p > .05$) indicated no significant differences between the observed and expected values of the dependent variable. The Nagelkerke R^2 statistic revealed that the model accounted for approximately 4.6% of the variation in the dependent variable. The model correctly classified 57.7% of the cases.

The Wald statistic associated with the ACT regression coefficient ($b = .091$; $SE = .003$) was statistically significant in the fitted model (Wald = 1,308.467, $p < .001$). The odds ratio revealed that some change in the probability of being retained could be attributed to ACT ($e^{.091} = 1.095$). A one-point increase in ACT composite score increased the odds of a student being retained by approximately 9.5%.

ACT Index Score

The simple regression model that included the ACT-index variable was also statistically significant in predicting retention (Model $\chi^2(1) = 666.040$, $p < .001$), although the model fit the data poorly (-2 Log L = 53,106.854). A non-significant Hosmer and Lemeshow test ($\chi^2(8) = 13.441$, $p > .05$) indicated no difference between the observed values of the dependent variable and the values expected from the logistic regression model. The Nagelkerke R^2 statistic revealed that the model accounted for approximately 2.3% of the

variation in the dependent variable. Overall, the model containing only the ACT-index variable fit the data less well and classified the cases less well than did the ACT-only model.

The regression coefficient for the ACT-index variable ($b = .014$; $SE = .001$) was a statistically significant predictor of retention (Wald = 649.224, $p < .001$), although the odds ratio associated with ACT-index ($e^{.014} = 1.014$) revealed a smaller change in the likelihood of retaining a student for each one-point increase than ACT. A one-point increase in a student's ACT-index score translated into a 1.4% greater likelihood that the student would be retained to the second year.

SAT-index.

The simple logistic regression model that included the computed SAT-index variable was also statistically significant in predicting retention (Model $X^2(1) = 696.696$, $p < .001$). The model fit the data statistically significantly better than the constant-only model ($-2 \text{ Log L} = 53,056.765$). A statistically significant Hosmer and Lemeshow test ($X^2(8) = 17.380$, $p < .001$) indicated that there was a statistically significant difference between the observed and expected values of the dependent variable—an indication that this model does not fit the data well. The Nagelkerke R^2 statistic revealed that the model accounted for approximately 2.4% of the variation in the dependent variable. This was approximately the same as the ACT-index, but considerably lower than the ACT-only model. Overall, the model containing only the SAT-index variable correctly classified 55.3% of the cases.

The SAT-index variable was a statistically significant predictor of retention ($b = .002$, $SE = .000$; Wald = 678.295, $p < .001$), although the odds ratio associated with ACT-index ($e^{.002} = 1.002$) revealed that an increase in the SAT-index score had little impact on the

probability of retaining a student. A one-unit increase in a student's SAT-index score translated into a .2% greater likelihood that the student would be retained to the second year.

Model Comparison

To test for statistically significant difference between fitted logistic regression models, two areas are examined. First, differences in goodness-of-fit between models may be tested using the change-in-chi-square test, which is described below. The change-in-chi-square test determines if statistically significant differences exist between the fit of two models. To test for statistically significant differences between the predictive power of two independent variables, a z-score transformation is utilized. The following section compares the simple logistic regression models, using a change-in-chi-square test to examine goodness-of-fit differences and the z-score transformation to examine predictive differences between ACT, ACT-index, and SAT-index variables.

Goodness-of-Fit Differences. The statistics presented in the previous section indicate the difference in goodness-of-fit for each fitted model and the constant-only model. To determine if the fitted models differ from each other, further analyses were necessary. Specifically, to determine if one model fit the data better than another, a change-in-chi-square test was performed. A change-in-chi-square test compares the model chi-square associated with each of the three fitted models. The difference between each pair of model chi-square values was compared to a chi-square table with one degree of freedom, setting $\alpha = .05$, and establishing a critical value of 3.841 (Freund & Wilson, 1997). A difference of more than 3.841, therefore, indicated that one model more closely fits the data. The differences are presented in Table 10.

The change-in-chi-square test for each logistic regression model revealed that the ACT-only model fit the data statistically significantly better than either the ACT-index model (change-in-chi-square = 705.951) or the SAT-index model (change-in-chi-square = 675.295). Further, the SAT-index model was statistically significantly better fitted to the data than was the ACT-index model (change-in-chi-square = 30.656).

Table 10. Simple Logistic Regression Model Chi-Square and Changes-in-Chi-Square Values

Model	Model X2	ACT-only	ACT-index	SAT-index
ACT-only	1371.991	--		
ACT-index	666.040	705.951 **	--	
SAT-Index	696.696	675.295 **	-30.656 **	--

*p < .05; **p < .001

Variable differences. Earlier in this chapter, Table 9 presented the regression coefficients, standard errors, Wald statistics, and odds-ratio for the ACT, ACT-index, and SAT-index variables from all three simple logistic regression models.

Table 11 presents the z-score transformations for the regression coefficients associated with ACT, ACT-index, and SAT-index for the respective models. To transform regression coefficients to z-scores the difference between the regression coefficients ($b_1 - b_2$) was divided by the square root of the sums of squares of the standard errors (SQRT ($SE_1^2 + SE_2^2$)). The result was a z-score that could be compared with a z-score table at alpha = .05 to

determine significant differences between the two coefficients. A z-score with an absolute value greater than approximately 2 indicated significant differences.

Four statistically significant differences were discovered. ACT was a statistically significantly stronger predictor of retention than the constant-only ($z = 8.428$, $p < .001$), ACT-index ($z = 24.35$, $p < .001$), and SAT-index ($z = 29.67$, $p < .001$) models. Further, ACT-index was statistically stronger than SAT-index ($z = 12.00$, $p < .001$).

Table 11. Simple Logistic Regression Z-Score Transformations for Independent Variables

	Constant-only	ACT-only	ACT-index	SAT-Index
Constant-only	--			
ACT-only	8.428 **	--		
ACT-index	-1.09	24.35 **	--	
SAT-Index	0.01	29.67 **	12.00 **	--

* $p < .05$, ** $p < .001$

Multiple Logistic Regression Analyses

The simple logistic regression models, while providing a direct comparison of the three variables, provide little useful information about retention because many likely significant variables deliberately have been removed from the model. Multiple logistic regression analysis allows for the variables of interest to be examined in a more realistic context.

Based on the literature reviewed in Chapter 2, the initial multiple regression analyses included the following independent variables: gender (GEN), race/ethnicity (RACE), age, estimated high school ranking (RANK), high school GPA (HS GPA), and Carnegie classification (CARN). Using a backward stepwise procedure, non-significant variables were removed, leaving a model with only significant predictor variables. In each case, the variable of interest (ACT, ACT-index, or SAT-index) remained in the final fitted model. This section compares the final fitted model and the influence of these variables on retention.

Model 1: ACT

The initial logistic regression analysis began with all independent variables (GEN, RACE, AGE, HS GPA, RANK, CARN, ACTAVE and ACT) included. GEN and AGE were removed from the final model as these variables failed to reach significance. Goodness-of-fit statistics indicated that the final model was significant ($-2 \text{ Log } L = 43,075.168$; Hosmer and Lemeshow $\chi^2 (8) = 45.285$; $\chi^2 (15) = 2,665.07$, $p < .001$). Model 1 therefore was significantly more predictive than the constant-only (B_0) model. The Nagelkerke R^2 statistic indicated that the model explained 10.3% of the variation found in the dependent variable. Overall, the model correctly classified 61.7% of observations.

Regression coefficients, Wald statistics, and odds ratios for the significant independent variables for Model 1 are presented in Table 12. Wald statistics indicated that several variables were statistically significant ($p < .05$) in the fitted model. Odds ratios for statistically significant independent variables, however, indicated that little change in the likelihood that a student would be retained could be attributed to any one independent variable.

Powerful predictors of retention in Model 1 included HSGPA (Wald (1) = 405.691; $p < .001$) and ACTAVE (Wald (1) = 411.416; $p < .001$). The odds ratio for HSGPA ($e^{.613} = 1.846$) indicated that the log odds ratio of the probability of retaining a student increases .613 for each one-point increase in HSGPA, and decreases .613 for each one-point decrease in HSGPA, controlling for other variables. Substantively, a one-point increase in HSGPA increases the odds of retaining a student by about 85%. ACTAVE proved to be another influential variable, with a one-point increase translating to a 16.3% increase in the probability of retention.

The odds ratio associated with a categorical variable, such as CARN, should be interpreted differently (Shelley, 1999). The categorical variable related to attending a Carnegie-classified Bachelor's/Liberal Arts (BA/LA) institution (Wald (1) = 26.722; $p < .001$), for example, was a powerful predictor of retention in this model. The odds ratio for CARN = BA/Gen ($e^{.676} = 1.966$) indicated that attending a BA/LA institution increased the odds of a student being retained about two times over attending a Bachelor's/General institution, the contrast variable.

ACT Composite Score. ACT composite score was a statistically significant variable in Model 1 (Wald (1) = 20.006; $p < .001$). The effect of ACT was positive ($b = .016$; SE = .003), generally indicating that an increase in ACT increased the odds of retaining a student, although not to a large degree. Specifically, the odds ratio ($e^{.016} = 1.016$) suggested that a one-point increase in ACT increases the odds of retaining a student by approximately 1.6%.

Table 12. Multiple Logistic Regression Model 1—ACT Composite Score

Variable	B	Wald	df	p	Odds Ratio
HSRANK		82.051	3	< 0.001	
1st Quarter	0.393	12.096	1	0.001	1.481
2nd Quarter	0.159	2.106	1	0.147	1.172
3rd Quarter	0.012	0.012	1	0.914	1.012
CARN		143.690	5	< 0.001	
DR EXT	0.118	5.539	1	0.019	1.126
DR INT	-0.143	5.573	1	0.018	0.867
MA I	-0.144	8.394	1	0.004	0.866
MA II	-0.133	1.694	1	0.193	0.876
BA LA	0.676	26.722	1	0.000	1.966
RACE		85.974	4	< 0.001	
Caucasian	0.137	3.441	1	0.064	1.146
African-American	0.519	37.012	1	0.000	1.680
Mexican-American/Hispanic	0.453	25.291	1	0.000	1.573
Asian-American/Pacific Islander	0.142	1.642	1	0.000	1.152
HSGPA	0.613	405.691	1	< 0.001	1.846
ACTAVE	0.151	411.416	1	< 0.001	1.163
ACT	0.016	20.006	1	< 0.001	1.016
Constant	-5.933	767.582	1	< 0.001	0.003
-2 Log L		4,3075.168			
Goodness-of-Fit X ²		45.285 **			
Nagelkerke R ²		0.103			
% Correctly Classified		61.7%			
Model X ²		2,665.070 **			

*p < .05, **p < .001

Model 2: ACT-Index

A similar backward stepwise logistic regression model was estimated for the same independent variables (GEN, RACE, AGE, HS GPA, RANK, CARN, and ACTAVE). For Model 2, however, ACT was replaced with the computed variable, ACT-index. Goodness-of-fit statistics indicated that the final model was significant ($-2 \text{ Log L} = 43,073.707$; Hosmer and Lemeshow $X^2(8) = 46.983$; $X^2(15) = 2,666.531$, $p < .001$), suggesting that Model 2 was significantly more predictive than the constant-only (B_0) model. The Nagelkerke R^2 statistic indicated that the model explained 10.3% of the variation found in the dependent variable. The model correctly classified 61.7% of observations.

Regression coefficients, Wald statistics, and odds ratios for the independent variables for Model 2 are presented in Table 13. Wald statistics indicated that several variables were statistically significant in the fitted model. GEN and AGE again failed to reach levels of significance and were removed from the final model. Odds ratios for statistically significant independent variables, however, indicated that little change in the likelihood that a student would be retained attributable to any one independent variable.

ACT-index. The independent variable ACT-index was a statistically significant predictor of retention in Model 2 (Wald (1) = 21.467; $p < .001$). The odds ratio associated with ACT-index ($e^{.004} = 1.004$) indicated that a one-unit increase in a student's ACT-index increased the probability that he or she would be retained by .4%, holding all other variables constant.

Table 13. Multiple Logistic Regression Model 2—ACT-Index Score

Variable	B	Wald	df	p	Odds Ratio
HSRANK		81.918	3	< 0.001	
1st Quarter	0.392	12.067	1	0.001	1.480
2nd Quarter	0.159	2.114	1	0.146	1.173
3rd Quarter	0.012	0.011	1	0.916	1.012
CARN		143.130	5	< 0.001	
DR EXT	0.117	5.438	1	0.020	1.125
DR INT	-0.144	5.633	1	0.018	0.866
MA I	-0.144	8.416	1	0.004	0.866
MA II	-0.0133	1.714	1	0.190	0.875
BA LA	0.676	26.748	1	< 0.001	1.967
RACE		86.607	4	< 0.001	
Caucasian	0.137	3.456	1	0.063	1.147
African-American	0.521	37.303	1	< 0.001	1.684
Mexican-American/Hispanic	0.454	25.456	1	0.001	1.575
Asian-American/Pacific Islander	0.142	1.653	1	0.119	1.153
HSGPA	0.612	404.567	1	< 0.001	1.844
ACTAVE	0.168	547.972	1	< 0.001	1.184
ACT-index	0.004	21.467	1	< 0.001	1.004
Constant	-6.304	767.618	1	< 0.001	0.002
-2 Log L		43,073.707			
Goodness-of-Fit X ²		46.983 **			
Nagelkerke R ²		0.103			
% Correctly Classified		61.7%			
Model X ²		2,666.531 **			

*p < .05, **p < .001

Model 3: SAT-Index

The backward stepwise logistic regression procedure that was completed on the same independent variables (GEN, RACE, AGE, HS GPA, RANK, CARN, and ACTAVE) and SAT-Index was statistically significantly better fitted to the data than the constant-only model as indicated by the goodness-of-fit statistics (-2 Log L = 43,061.187; Hosmer and Lemeshow $\chi^2(8) = 47.527$; $\chi^2(15) = 2,662.04$, $p < .001$). The Nagelkerke R^2 statistic indicated that the model explained 10.3% of the variation found in the dependent variable. The model correctly classified 61.7% of the cases.

Regression coefficients, Wald statistics, and odds ratios for the independent variables for Model 3 are presented in Table 14. Wald statistics indicated that several variables were statistically significant in the fitted model. GEN and AGE again failed to reach levels of significance and were removed from the final model. Odds ratios for statistically significant independent variables, however, indicated little change in the likelihood that a student would be retained could be attributed to any one independent variable.

SAT-Index. The regression coefficient for SAT-Index ($b = .000$; $SE = .000$) reached the .001 level of statistical significance (Wald = 18.775; $p < .001$). The significant finding, however, likely was due to sample size, as the impact was not detectable to three decimal places ($e^{.000} = 1.000$). Any impact on retention that is directly attributable to changes in the SAT-index was negligible.

Model Comparison

The three fitted logistic regression models were examined for statistically significant differences in goodness-of-fit and predictive power of ACT, ACT-index, and SAT-index variables. The results of those comparisons are presented in this section.

Table 14. Multiple Logistic Regression Model 3—SAT-Index Score

	B	Wald	df	p	Odds Ratio
HSRANK		82.690	3	< 0.001	
1st Quarter	0.392	12.051	1	0.001	1.480
2nd Quarter	0.157	2.061	1	0.151	1.170
3rd Quarter	0.010	0.008	1	0.928	1.010
CARN		144.677	5	< 0.001	
DR EXT	0.118	5.522	1	0.019	1.126
DR INT	-0.144	5.668	1	0.017	0.866
MA I	-0.146	8.543	1	0.003	0.865
MA II	-0.134	1.716	1	0.190	0.875
BA LA	0.676	26.688	1	< 0.001	1.965
RACE		87.415	4	< 0.001	
Caucasian	0.136	3.427	1	0.064	1.146
African-American	0.522	37.466	1	< 0.001	1.686
Mexican-American/Hispanic	0.456	25.684	1	< 0.001	1.578
Asian-American/Pacific Islander	0.141	1.629	1	0.202	1.151
HSGPA	0.615	407.607	1	< 0.001	1.850
SATAVE	0.004	545.279	1	< 0.001	1.004
SAT-index	0.000	18.775	1	< 0.001	1.000
Constant	-6.526	790.783	1	< 0.001	0.001
-2 Log L	43,061.187				
Goodness-of-Fit X ²	47.527 **				
Nagelkerke R ²	0.103				
% Correctly Classified	0.617				
Model X ²	2,662.042 **				

*p < .05, **p < .001

Goodness-of-Fit Comparisons. Change-in-chi-square tests were conducted to compare the model fit of across models. Table 15 presents the model chi-square values associated with all three models and the changes-in-chi-square values. Again, assuming one degree of freedom, a change with absolute value greater than 3.84 would be considered significant at the .05 level.

No statistically significant difference was found between Model 1 and Model 2 or between Model 1 and Model 3. Thus, the models that included the ACT-index variable or the SAT-index variable fit the data equally as well as the model that included the ACT variable. Statistically significant differences were found between Model 3 and Model 2 (change-in-chi-square = 4.489, $p < .05$). The model that contained the SAT-index variable did not fit the data as well as the model containing the ACT-index variable.

Table 15. Multiple Logistic Regression Model Change-in-Chi-Square Analysis

	Model Chi-Square	ACT	ACT-index	SAT-Index
ACT	2,665.070	--		
ACT-index	2,666.531	-1.461	--	
SAT-Index	2,662.042	3.028	4.489 *	--

* $p < .05$

Variable Differences. Table 16 contains the regression coefficients, standard errors, and z-scores associated with the three variables of interest from the multiple regression

models. Again, z-scores greater than two indicates a statistically significant difference in predictive ability for the independent variable.

Z-score analyses revealed that ACT was statistically significantly more powerful a predictor than was ACT-index ($z = 2.910$, $p < .05$) or SAT-index ($z = 4.00$, $p < .001$). The ACT variable thus predicted retention better than either of the merit indices. Further, the ACT-index statistically significantly predicted retention better than the SAT-index ($z = 4.00$, $p < .001$).

Table 16. Multiple Logistic Regression Independent Variable Z-Score Transformations

Model	Regression Coefficients	Standard Error	ACT	ACT-index	SAT-Index
ACT	0.016	0.004	--		
ACT-index	0.004	0.001	2.910 *	--	
SAT-Index	0.000	0.000	4.000 *	4.000 *	--

* $p < .05$

Results by Racial Category

After finding the most predictive retention models (Models 1-3 presented above), the current sample was split by racial category. Each model was run exclusively for each racial group and the results examined for differences. The results are presented in this section.

Model Comparison

Comparison of the resulting regression models was conducted two ways. First, a within-model comparison was conducted to determine the differences between each model for the different racial categories. That is, the power of ACT as a predictor in Model 1 for Caucasian students was compared with the power of ACT for African-American students. Second, the predictive power of each model for the different racial categories was compared—a between-model comparison. For example, the predictive power of the ACT (Model 1) for Caucasian students was compared with the predictive power of the ACT-index (Model 2) for Caucasian students. A z-score transformation, as described earlier, was used to examine the differences between independent variables.

Within-Model Comparisons

Odds ratios for each model by racial group are presented in Table 17. As is noted in the table, the achievement variables under consideration (ACT, ACT-index, and SAT-index) were not statistically significant predictors of retention for the Mexican-American/Chicano/Hispanic, Asian-American/Pacific Islander, or Multiracial/Other groups. In fact, SAT-index failed to reach significance for any racial group. The ACT and ACT-index variables were significant predictors for Caucasian and African-American racial groups. Differences between the statistically significant variables are discussed in this section.

Model 1: ACT. The ACT variable was a significant predictor for Caucasian and African-American racial groups. Odds ratio ($e^{.019} = 1.019$) indicated that, in Model 1, a one-point increase in ACT resulted in a 1.9% increase in the likelihood a Caucasian student was retained. For African-American students in Model 1, the odds ratio ($e^{.031} = 1.031$) resulted in a 3.1% increase in the likelihood of retention.

Table 17. Odds Ratios for ACT, ACT-Index, and SAT-Index for Racial Categories

Racial Category	ACT	ACT-Index	SAT-Index
Caucasian	1.019 **	1.004 **	1.000
African-American	1.031 *	1.006 *	1.001
Mexican-American/Hispanic	0.996	1.000	1.000
Asian-American/Pacific Islander	0.972	0.994	0.999
Multiracial/Other	0.986	0.997	1.000

* $p < .05$, ** $p < .001$

A z-score transformation indicated that no statistically significant differences existed between the regression coefficients for ACT in the Caucasian-only and African-American-only models ($z = -.773$; $p > .05$). That is, ACT appeared to predict retention equally well for both racial categories. Within-model z-score transformations for both models are presented in Table 18.

Model 2: ACT-Index. ACT-index was also a statistically significant predictor of retention for both Caucasian and African-American students, although the odds ratio for both indicated that it was much less powerful than ACT (Table 17). The odds ratio for ACT-index in the Caucasian-only model ($e^{.004} = 1.004$) indicated that a one-point increase in ACT-index resulted in a 0.4% increase in the likelihood a Caucasian student would be retained. For African-American students under Model 2, the odds ratio ($e^{.006} = 1.006$) translated into a .6% increase in the likelihood of retention for every one-point increase in ACT-index score.

Table 18. Within-Model Z-scores for ACT and ACT-Index by Race

	Caucasian Students	African-American Students	Within-Model Z-Scores
Model 1			
Regression Coefficients	.019	.031	-0.773
Standard Error	.004	.015	
Model 2			
Regression Coefficients	.004	.006	-0.663
Standard Error	.001	.003	

Z-scores were computed for the regression coefficients and presented in Table 18.

The Z-score indicated again no statistically significant difference in ACT-index prediction of retention for the Caucasian-only sample or the African-American-only sample ($z = -.6325$; $p > .05$). ACT-index appears to be equally predictive of both racial categories.

Between-Model Comparisons

The previous section compared the regression coefficients for Caucasian and African-American students for each model run on racially split samples. This analysis allowed us to draw conclusions regarding the predictive power of a variable for each racial group, using the other racial group for comparison. The following section compares the regression coefficients between models to determine if one variable predicted retention better than the other variable for a specific racial category. That is, the regression coefficient for ACT in

Model 1 run on the African-American-only sample will be compared with the regression coefficient for ACT-index in model two run on the same population.

A z-score transformation allows for the between model comparison of regression coefficients. The results, presented in Table 19, allow for the formulation of conclusions regarding the predictive ability of each model for the two racial categories.

Caucasians. A comparison of the regression coefficient for ACT in Model 1 run on the Caucasian-only sample ($b = .019$, $SE = .004$) and the regression coefficient for ACT-index in Model 2 run on the same sample ($b = .004$, $SE = .001$) revealed a statistically significant difference ($Z = 3.638$, $p < .05$). This finding indicated that ACT was a better predictor of retention than ACT-index for Caucasian students.

African-Americans. A comparison of regression coefficients for ACT ($b = .031$, $SE = .015$) and ACT-index ($b = .006$, $SE = .003$) for the African-American-only sample revealed no statistically significant differences between the two variables ($Z = 1.634$, $p > .05$). ACT and ACT-index scores appear to be equally predictive for Caucasian and African-American students.

Table 19. Between-Model Z-scores for ACT and ACT-Index by Race

	Model 1 Regression Coefficients	Model 1 Standard Error	Model 2 Regression Coefficients	Model 2 Standard Error	Between Model Z- Scores
Caucasian-only	0.019	0.004	0.004	0.001	3.638 *
African- American-only	0.031	0.015	0.006	0.003	1.634

Chapter 5. Summary, Conclusions, and Recommendations

The purpose of the study was to assess the efficacy of two merit-index measures, as they related to the ACT Composite score, in predicting undergraduate college student first-to-second year retention. Specifically, this study explored the ACT-index and the SAT-index measures. This final chapter summarizes the results of the research study. This chapter is organized in five sections: 1) Summary, 2) Conclusions, 3) Discussion, and 4) Recommendations for Further Research.

Summary

The researcher employed quantitative research methods to explore data gathered by, and obtained from, ACT, Inc. The data represented all students who sat for the ACT Assessment during the 1999 test administration period and whose higher education institution participated in a retention study conducted by ACT, Inc. A large sample size ($n = 39,216$) was selected from an original database of 87,915 cases.

Descriptive and inferential statistics were used to analyze the data. Frequencies and percentages were used to describe categorical demographic variables, while means and standard deviations were presented to describe continuous variables. Correlation data were presented to further examine the relationship between all variables.

The researcher employed logistic regression analysis as the primary inferential statistical technique in this research. Logistic regression procedures regressed the dichotomous dependent variable, retention, onto several predictor variables. Simple regression models, each including only the three measures of interest (ACT, ACT-index, and

SAT-index), and backward stepwise logistic regression models, including all identified variables, were utilized to explore the data.

Findings

Based upon the data analysis described above, the major findings of the study included:

1. ACT predicted between-year retention better than the ACT-index.
2. The ACT-index was a better predictor of between-year retention than the SAT-index in this study.
3. ACT Composite and ACT-index only significantly predicted between-year retention in Caucasian and African-American students. All three variables (ACT, ACT-index, and SAT-index) failed to significantly predict retention in Asian-American/Pacific Islander, Mexican-American/Chicano/Hispanic, or Multiracial/Other students.
4. Gender of the student was not a significant predictor variable in the fitted regression models. Unlike Astin's (1977, 1997) or Tinto's (1987) conclusions, women in this study were not more likely to be retained than men. This finding supports more recent research, however, regarding the lessening relationship between gender and retention (Peltier et al., 1999; St. John et al., 2001).
5. Age of respondent did not reach significance as a predictor of retention. This finding also contradicted Astin's (1977, 1997) research on student retention.
6. The average ACT score of a student's high school class (ACTAVE) was a significant predictor of between-year retention in each multiple regression

model estimated in this inquiry. If it is assumed that ACTAVE served as a proxy variable of the quality of a student's high school, this finding seemingly supports the argument posited by Adelman (1999, 2000) regarding the role of secondary school quality in predicting college and university retention.

Conclusions

The findings of this investigation hold implications for enrollment management personnel and contradict the findings of similar research conducted by other researchers (St. John et al., 2001). The results indicate that using the more traditional assessment measure, ACT Composite score, remains the most effective way to predict retention among college students. The findings of the investigation are presented below according to the four research questions and two hypotheses presented in Chapter 1.

Research Questions and Hypotheses

The researcher framed this inquiry by asking four research questions and positing three hypotheses. The research questions guided the inquiry and the answers to these questions became the major conclusions of the study. The three hypotheses accompanied the research questions, and provided testable conclusions. The questions and hypotheses are presented and discussed in this section.

Question 1

Based on the results of backward stepwise regression model analyses, what model best fits the data examined? Three backward stepwise regression analyses were completed. Each regression analysis began with the same independent variables. The independent variables included gender, age, race, high school GPA, high school rank, Carnegie classification of the higher education institution, and average ACT composite score of each

students' high school class, along with the ACT, ACT-index, or SAT-index. In each backward regression model, gender and age failed to reach significance and were removed, leaving the other independent variables in the final model.

A series of statistical procedures were used to examine the fit of each regression model to the data. These procedures included examinations of the model based upon the -2 Log L test, Hosmer and Lemeshow Goodness-of-Fit chi-square test, the Model chi-square test, Nagelkerke pseudo- R^2 , and the classification table. Based upon this series of statistical procedures, no model appeared to fit the data better than the others, although the relative importance of individual predictor variables changed. Each fitted regression model, however, predicted retention better than the constant-only model that was used for comparison.

Question 2

Does the ACT-index score, formulated to consider the level of achievement of a student in relation to his or her peers, predict between-year retention as well as the more traditional ACT Composite score? In neither the simple regression analyses nor the multiple regression analyses did the ACT-index score predict between-year retention as well as ACT. Using the odds-ratio of each independent variable as an indicator of predictive ability showed that, in the simple regression models, ACT ($e^b = 1.095$) was approximately four times stronger than the ACT-index ($e^b = 1.014$). Similarly, in the multiple regression models, ACT ($e^b = 1.016$) was four times stronger than the ACT-index variable ($e^b = 1.004$).

Question 3

Does the ACT-index score predict between-year retention as well as the SAT-index, as defined by St. John and others (2001)? The ACT-index appeared to out perform the SAT-index in predicting between-year retention in the simple and multiple regression models.

Again, using odds-ratios as indicator of predictive power, the ACT-index ($e^b = 1.014$) was much more predictive than the SAT-index ($e^b = 1.002$) in the simple regression models. In the multiple regression models, the ACT-index ($e^b = 1.004$) also predicted between-year retention better than the SAT-index ($e^b = 1.000$), which appeared to only minimally effect retention.

Question 4

Do differences exist between the three scores (ACT, ACT-index, and SAT-index) for the different racial categories in the sample? To examine this question, the dataset was split by racial categories and each of the three fitted multiple regression models run. Differences were found. First, SAT-index failed to reach a significant level for any racial category. ACT and ACT-index were statistically significant in predicting retention for Caucasians and African-American students only. Only statistically significant variables were considered for further comparison.

Within- and between-model comparisons of the regression coefficients were conducted to for differences. These tests provided mixed results. Using a within-model comparison of ACT (comparing the predictive power of ACT for Caucasians to its predictive power for African-Americans), ACT appeared to predict retention equally well for Caucasians and African-Americans. A similar conclusion was made from the within-model comparison of ACT-index.

Between-model comparisons of regression coefficients compared ACT to ACT-index for each racial category. Z-tests revealed that ACT was statistically significantly better than the ACT-index at predicting retention for Caucasian students. On the other hand, no statistically significant difference was found in the regression coefficients for ACT and ACT-

index for African-American students. Evidence supports a conclusion that ACT and ACT-index are equally predictive of retention for African-American students.

Hypothesis

There is no statistically significant difference between the fit of a retention model using ACT-index and a model using the ACT Composite score. A change in chi-square test that compared model chi-square for each model against a chi-square table with one degree of freedom found the ACT-only simple logistic regression model better fit the data than the ACT-index simple regression model ($p. < .05$). The null hypothesis that no difference existed was therefore rejected. The ACT-only model was statistically significantly better in predicting between-year retention than the ACT-index simple logistic regression.

Hypothesis

There is no statistically significant difference between fit of a retention model using SAT--index and a model using the ACT Composite score. A change in chi-square test again rejected the null hypothesis ($p. < .05$) that there was no difference existed in the fit of these two models. The ACT-only model was statistically significantly better in predicting between-year retention than the SAT-index simple logistic regression.

Hypothesis

There is no statistically significant difference between the predictive power of a retention model that uses the ACT-index score and one that uses the SAT-index score. Again, a change-in-chi-square test was used to test this hypothesis using the simple logistic regression models. Statistically significant differences were found ($p. < .05$) between the ACT-index model and the SAT-index model. The null hypothesis was therefore rejected. Evidence suggests that the ACT-index model fit the data better than the SAT-index model.

Summary

Evidence regarding the predictive capabilities of the ACT Composite score, the ACT-index score, and the SAT-index score is mixed. The ACT score appears to predict retention equally well for Caucasians and African-American students. Similarly, the ACT-index score appears to predict retention equally well for Caucasians and African-American students. Evidence supports that the ACT-index is equally as predictive as the ACT for predicting retention for African-American students.

On the other hand, it is important to note SAT-index was not a significant predictor in any of the racially divided models conducted. Furthermore, ACT and ACT-index failed to reach significance for the Asian-American/Pacific Islanders, the Mexican-American/Chicano/Hispanic, and the Multiracial/Other categories. These findings should cause concern for anyone making retention predictions for students in these racial groups.

Discussion

St. John and his colleagues (2001) concluded, “using the [SAT-based] merit index in admissions would not only improve diversity but also maintain [retention] rates” (p. 149). This conclusion was based on a finding that the merit-index predicted retention equally well as the SAT score alone. The current study attempted to replicate these findings using ACT-based data. The results question St. John et al.’s findings regarding both the maintenance of retention rates and the improvement of diversity among undergraduate college students.

Maintaining Persistence Rates

The current research findings question, if not contradict, the findings of St. John and colleagues (2001) regarding persistence rates and merit-indices. The ACT Composite score

appeared to be the most predictive measure of the three under examination (ACT, ACT-index, and SAT-index) in this investigation. Odds ratios for the ACT Composite score variable were consistently larger than odds ratios for ACT-index or SAT-index variables, indicating a stronger predictive relationship with retention. The ACT-index reached levels of significance in both the simple and multiple regression models, but the odds ratios associated with the variable indicated little or no effect on retention. The SAT-index, although significant, had no effect on retention in the multiple regression analysis.

Based on the simple and multiple logistic regression analyses presented in this paper, one can only conclude that the measures of merit-indices should not replace the ACT Composite score as a predictor of retention.

Improving Diversity

A second component the argument in favor of merit-indices (Cooper, 1999; St. John et al., 2001) is that the use of merit-indices would increase the racial diversity of undergraduate students. Cooper offered the merit-index measure as a response to attacks on affirmative action. The theory underlying this argument is sound. If the differential between a student's score and his or her high school's average score on a standardized test was equally predictive of retention as the standardized test score, regardless of the high school average, students from lower performing high schools, with equally large differential scores (merit-indices) should be admitted and retained. The research presented herein did not support this theory.

Examining the three multiple regression models on a dataset split by racial category revealed several differences that call into question the assumptions about improving racial diversity. First, and foremost, the measures under consideration were not significant

predictors of retention for all races. The SAT-index failed to reach significance for any racial category, while the ACT and ACT-index only predicted retention in Caucasians and African-Americans. Predicting retention for other racial groups remains dubious when using any of these three variables. Mexican-, Asian-, and Multiracial-Americans are not likely to benefit due to the implementation of a merit-index based admissions procedure.

Recommendations for Future Research

The findings of the current research prompt several questions deserving of future consideration and inquiry. The ACT-index measure warrants further examination, especially related to retention for the different racial categories included in this study. ACTAVE as a predictor of between-year retention holds promise and should be explored further.

ACT-Index

Future researchers should continue to explore the efficacy of the ACT-index measure as a predictor of retention. The theory underscoring such merit indices, as presented by Cooper (1999) for example, proposes an answer to attacks on affirmative action in college and university admissions policies. If maintaining a racially and culturally diverse college population remains a goal of college and university administrators, then finding a merit index measure that does as Cooper purports is necessary.

The ACT-index measure was a significant predictor of between-year retention for Caucasians and African-Americans. Although the ACT-index measure was not as powerful as the ACT composite score, the significant relationship between ACT-index and retention in these two racial groups finding is promising for policy makers. Researchers must answer questions related to why the ACT-index was significant for these two racial groups, but failed to reach significance for others.

Retention Predictors for Other Racial Categories

In general, predicting retention for Asian-American/Pacific Islander students, Mexican/Chicano/Hispanic students, and multiracial students should be examined further. None of the measures of interest (ACT, ACT-index, and SAT-index) significantly predicted retention in these racial/ethnic categories. If, as researchers predict, the percentage of college students from these populations continues to increase (Keller, 2001; Pascarella & Terenzini, 1998; Woodard, Love, & Komives, 2000b), college administrators and researchers should endeavor to determine which variables most efficiently and powerfully predict retention for students identifying with racial categories other than Caucasian or African-American.

ACTAVE as a Predictor of Retention

The average ACT score of a student's high school class (ACTAVE) remained a significant predictor in all multiple regression models. Further inquiry into this variable as a predictor of retention is warranted. If, as Adelman (1999, 2000) proposed, the quality of a student's high school academic experience is the leading predictor of his or her success in college, ACTAVE could serve as a readily available proxy for high school quality. Before such a policy decision is made, however, research must confirm and validate the findings of this study.

Appendix. ACT to SAT Conversion and Concordance Table

Appendix A: ACT to SAT Conversion and Concordance Table

The original data set used in this study came from ACT, Inc and consisted of variables related to the ACT Assessment. In order to compare findings of this study with findings of similar research by St. John and his colleagues (2001), ACT scores were converted to their SAT equivalents. Appendix A explains the steps that were taken to convert ACT-related variables to their SAT-equivalents.

Individual Case Variables

ACT variables related to each student included ACT scores for four subsections of the assessment and the overall composite score. The first step in converting ACT scores to SAT-equivalent scores was to convert the individual ACT composite variables to SAT scores using a concordance table available through the SAT website (College Board, 2001). Table 20 presents the ACT composite to SAT verbal plus math equivalent scores.

SAT-Index Measure

St. John and colleagues (2001) defined the SAT-index measure as the differential of the individual's SAT score and the average SAT score for his or her high school class. A similar definition was assumed for this study. Therefore, after computing the individual SAT composite score, the SAT average was needed for each student's high school class. The following section explains how the SAT average was derived.

SAT Average

To determine the average SAT composite score for each student's high school class, it was necessary to establish a relationship between the ACT composite score variable, which was included in the original dataset, and the SAT composite score variable, which was determined from the concordance table discussed above.

Table 20. ACT Composite Score to SAT-Equivalent Concordance Table

ACT Composite Score	SAT Score (Verbal + Math)
36	1600
35	1580
34	1520
33	1470
32	1420
31	1380
30	1340
29	1300
28	1260
27	1220
26	1180
25	1140
24	1110
23	1070
22	1030
21	990
20	950
19	910
18	870
17	830
16	780
15	740
14	680
13	620
12	560
11	500

A simple linear regression analysis was completed with the SAT composite score as the dependent variable and the ACT composite score as the independent variable. Based on the results of the analysis, a linear relationship between SAT and ACT composite scores was established. The fitted regression equation took the form

$$\text{SAT Composite} = 141.779 + 40.163 (\text{ACT Composite}).$$

A linear estimate of the average SAT test score for each student's high school was then derived by inserting the ACT average variable, from the original data set, into the equation.

SAT-Index Measure

As stated previously, St. John and his colleagues (2001) defined the SAT-index as the difference between a student's individual SAT composite score and the average SAT composite score for his or her high school class. A simple subtraction equation thus was completed to compute SAT-index for this study:

$$\text{SATINDEX} = \text{SAT composite} - \text{SAT average}.$$

The SAT-index measure assumes a range from -1600 to +1600. A positive SAT-index indicates that a student scored above the average of his or her peers, while a negative SAT-index indicates that the student scored below the average.

With this final computation completed, the SATINDEX variable could be included in the logistic regression analysis.

References

ACT, Inc. (2001a). ACT Research [On-line]. Available: <http://www.act.org/research>

ACT, Inc. (2001b). Understanding your ACT score [On-line]. Available:

<http://www.act.org/aap/scorres/under.html>

Adelman, C. (1999). Answers in the toolbox: Academic intensity, attendance patterns, and bachelor's degree attainment. Washington, DC: U. S. Department of Education, Office of Educational Research and Improvement.

Adelman, C. (2000). Let's stop talking about the SAT. Trusteeship, 8, 23-27.

Agresti, A. (1990). Categorical data analysis. New York: John Wiley & Sons.

Agresti, A. (1996). An introduction to categorical data analysis. New York: John Wiley & Sons.

Allen, D. (1999). Desire to finish college: An empirical link between motivation and persistence. Research in Higher Education, 40, 461-485.

Allison, P. D. (1999). Logistic regression using the SAS[®] system: Theory and application. Cary, NC: SAS Institute.

Astin, A. W. (1964). Personal and environmental factors associated with college dropouts among high aptitude students. Journal of Educational Psychology, 55, 276-287.

Astin, A. W. (1975). Preventing students from dropping out. San Francisco: Jossey-Bass.

Astin, A. W. (1997). How 'good' is your institution's retention rate? Research in Higher Education, 38, 647-658.

Astin, A. W., Korn, W., & Green, K. (1987). Retaining and satisfying students. Educational Record, 68, 36-42.

Bayer, A. E. (1968). The college dropout: Factors affecting senior college completion. Sociology of Education, 41, 305-316.

Blose, G. (1999). Modeled retention and graduation rates: Calculating expected retention and graduation rates for multicampus university systems. In G. H. Gaither (Ed.), Promising practices in recruitment, remediation, and retention (pp. 69-86). (New Directions for Higher Education, n. 108) San Francisco: Jossey-Bass.

Braxton, J. M. (2000). Reworking the student departure puzzle. In J. M. Braxton (Ed.), Reworking the Student Departure Puzzle (pp. 1-10). Nashville, TN: Vanderbilt University.

Braxton, J. M., & Lien, L. A. (2000). The viability of academic integration as a central construct in Tinto's interactionist theory of college student departure. In J. M. Braxton (Ed.), Reworking the student departure puzzle (pp. 22-28). Nashville, TN: Vanderbilt University.

Carnegie classification database (2000). Chronicle of Higher Education [On-line]. Available: <http://chronicle.com/stats/carnegie/>

College Board (2001). ACT to SAT concordance tables [On-line]. Available: <http://www.collegeboard.org/sat/cbsenior/html/stat00f.html>

Cooper, K. J. (1999). Admissions models for inclusion. Black Issues in Higher Education, 16, (18), 34-35.

Davidson, B. S., & Muse, C. T. (1994). A ten-year longitudinal study comparing 1980 freshmen students' persistence to graduation at two selected universities. (ERIC Document Reproduction Service No. ED 372 682).

Dale, P. M., & Zych, T. (1996). A successful college retention program. College Student Journal, 30, 354-360.

Dey, E. L., & Astin, A. W. (1993). Statistical alternatives for studying college student retention: A comparative analysis of logit, probit, and linear regression. Research in Higher Education, 34, 569-581.

Freund, R. J., & Wilson, W. J. (1997). Statistical methods (Rev. ed.). San Diego, CA: Academic Press.

Gall, M. D., Borg, W. R., & Gall, J. P. (1996). Education research: An introduction (6th ed.). White Plains, NY: Longman.

Gloria, A. M., Robinson Kurpius, S. E., Hamilton, K. D., & Willson, M. S. (1999). African American students' persistence at a predominantly white university: Influences of social support, university comfort, and self-beliefs. Journal of College Student Development, 40, 257-268.

Green, S. B., Salkind, N. J., & Akey, T. M. (2000). Using SPSS for Windows: Analyzing and understanding data (2nd ed.). Upper Saddle, NJ: Prentice Hall.

Hall, C. (1999, May). African American college students at a predominantly white institution: Patterns of success. Paper presented at the meeting of the Association of Institutional Research, Seattle, WA.

Hosmer, D. W., & Lemeshow, S. (1989). Applied logistic regression. New York: John Wiley and Sons.

Keller, G. (2001). The new demographics of higher education. The Review of Higher Education, 24, 219-236.

Levitz, R. S., Noel, L., & Richter, B. J. (1999). Strategic moves for retention success. In G. H. Gaither (Ed.), Promising practices in recruitment, remediation, and retention (pp. 31-50). (New Directions for Higher Education, n. 108) San Francisco: Jossey-Bass.

Mertler, C. A., & Vannatta, R. A. (2001). Advanced and multivariate statistical methods: Practical application and interpretation. Los Angeles: Pyrczak.

Michelle, D. F., Goldman, B. A., & Smith, M. (1999). Change factors affecting college matriculation: A re-analysis. Journal of the First-Year Experience and Students in Transition, 11, 75-92.

Moxley, L. S. (1999). Student affairs research and evaluation: An inside view. Student affairs research, evaluation, and assessment: Structure and practice in an era of change (pp. 11-22). (New Directions for Student Services, no. 85) San Francisco: Jossey-Bass.

Murdock, S. H., & Nazrul Hoque, Md. (1999). Demographic factors affecting higher education in the United States in the twenty-first century. In G. H. Gaither (Ed.), Promising practices in recruitment, remediation, and retention (pp. 5-14). New Directions for Higher Education, no.108) San Francisco: Jossey-Bass.

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

National Center for Education Statistics (NCES; 2001a). The digest of education statistics [On-line]. Available: <http://nces.ed.gov/pubs/2001/digest>

National Center for Education Statistics (NCES; 2001b). Fast Facts Web page [On-line]. Available: <http://nces.ed.gov/fastfacts/display.asp?id=72>

Neter, J., Kutner, M. H., Nachtsheim, C. J., & Wasserman, W. (1996). Applied linear regression models (3rd ed.). Chicago: Irwin.

Newman, P. R., & Newman, B. M. (1999). What does it take to have a positive impact on minority students' college retention? Adolescence, 34, 483-492.

Norusis, M. J. (1999). SPSS Regression Models™10.0. Chicago: SPSS, Inc.

Parker, C. (1999). Who really cares about retention? Black Issues in Higher Education, 16, (18), 144.

Pascarella, E. T., & Terenzini, P. T. (1998). Studying college students in the 21st century: Meeting new challenges. The Review of Higher Education, 21, 151-165.

Peltier, G. L., Laden, R., Matranga, M. (1999). Student persistence in college: A review of research. Journal of College Student Retention, 1, 357-376.

Roach, R. (1999). The state of retention. Black Issues in Higher Education, 16, (18), 28-29.

Sawyer, R., & Brounstein, P. (1988, April). The relationship between ACT and SAT scores among academically talented seventh grade students. Paper presented at the Annual Meeting of the National Council on Measurement in Education, New Orleans, LA.

Shelley, M. C. (1999). Multivariate techniques for dichotomous dependent variables. In G. J. Miller & M. L. Whicker (Eds.), Handbook of research methods in public administration (pp. 409-452). New York: Marcel Dekker.

St. John, E. P., Hu, S., Simmons, A. B., & Musoba, G. D. (2001). Aptitude vs. merit: What matters in persistence. The Review of Higher Education, 24, 131-152.

Sweet, S. A. (2000). Data analysis with SPSS®. Boston: Allyn & Bacon.

Tabachnick, B. G., & Fidell, L. S. (1996). Using multivariate statistics (3rd ed.). New York: Harper Collins.

Texas Education Agency (2000). Results of college admissions testing in Texas for 1998-99 graduating seniors (Publication No. GE00-601-04). Austin, TX: Texas Education Agency.

Tinto, V. (1975). Dropout from higher education: A theoretical synthesis of recent research. Review of Educational Research, 45, 89-125.

Tinto, V. (1987). Leaving college: Rethinking the causes and cures of student attrition. Chicago: University of Chicago Press.

Tinto, V. (1996). Reconstructing the first year of college. Planning for Higher Education, 25, 1-6.

Tross, S. A., Harper, J. P., Osher, L. W., & Kneidinger, L. M. (2000). Not just the usual cast of characteristics: Using personality to predict college performance and retention. Journal of College Student Development, 41, 323-334.

Vaughan, R. P. (1968). College dropouts: Dismissed vs. withdrew. Personnel and Guidance Journal, 46, 985-689.

Wolfe, R. N., & Johnson, S. D. (1995). Personality as a predictor of college performance. Educational and Psychological Measurement, 55, 177-185.

Woodard, D. B., Love, P., & Komives, S. R. (2000a). Learning and development. In D. B. Woodard, P. Love, & S. R. Komives (Eds.), Leadership and management issues for a new century (pp. 49-60). (New Directions for Student Services, no. 92) San Francisco: Jossey-Bass.

Woodard, D. B., Love, P., & Komives, S. R. (2000b). Students of the new millennium. In D. B. Woodard, P. Love, & S. R. Komives (Eds.), Leadership and management issues for a new century (pp. 35-47). (New Directions for Student Services, no. 92) San Francisco: Jossey-Bass.

Zusman, A., Fox, W. H., Gerth, D. R., & Coleman, L. B. (2000, November). Meeting the challenges of "Tidal Wave II": Educating a half million more Californians in the next decade. Symposium conducted at the Annual Graduate Seminar on Higher Education Policy of the Association for the Study of Higher Education, Sacramento, CA.

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No man has earned the right to intellectual ambition until he has learned to lay his course by a star which he has never seen—to dig by the divining rod for springs which he may never reach...Only when you have worked alone—when you have felt around you a black gulf of solitude more isolating than that which surrounds the dying man, and in hope and in despair have trusted to your own unshaken will—then only will you have achieved. Thus only can you gain the secret isolated joy of the thinker, who knows that, a hundred years after he is dead and forgotten, men who never heard of him will be moving to the measure of his thoughts—the subtile rapture of a postponed power, which the world knows not because it has no external trappings, but which to his prophetic vision is more real than that which commands an army.

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