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LEARNING, INSTRUCTION, AND COGNITION

Teaching Learning Strategies to Increase Success of First-Term College Students

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In this study, the authors examined the effect of taking a learning strategies course on grade point average, retention, and graduation rate of 351 first-year students over their first 4 terms in comparison with 351 matched non–course takers. The course taught 4 learning strategies and 8 substrategies to help students overcome procrastination, build self-confidence, take responsibility, learn from lecture and text, prepare for exams, write papers, and manage their lives. First-year students who took the course in their first term had statistically significantly higher grade point averages in each of their first 4 terms. They also demonstrated statistically significantly higher retention rates and were six times more likely to be retained. In addition, they had statistically significantly higher graduation rates than did their matched controls. In particular, graduation rates were 50% higher for students initially in academic difficulty. These findings reveal the value of teaching learning strategies to first-year students by means of a structured course based on educational psychology. This research holds potential importance for other universities and colleges seeking to improve the performance and persistence of first-year students.

Keywords: achievement, cognitive processes/development, college students, computer education/computer-assisted learning, instructional design/development, learning processes/strategies, motivation

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GETTING INTO COLLEGE and then dropping out is a problem at postsecondary education institutions, even among students who enter with high school records that would appear to predict college success. On a national basis, the university dropout rate is about 25% and community college dropout rate 50%, with the majority in both locations occurring in the first year. Among urban minority students who enroll in college, 55% choose community colleges often because of their easy accessibility, low cost, broad-based admission policies, and diversity of program offerings, yet only 50% remain in school (American Association of Community Colleges, 2002). The magnitude of the retention problem in community colleges is exacerbated by their current growth rate.

Innovative reforms must be implemented that remove barriers to academic success, most notably students' lack of motivation and relevant learning strategies. Hadwin and Winne (1996) advocated that "institutions should provide means for students to develop adaptable strategies with which to pursue knowledge and solve problems during and after postsecondary experiences" (p. 693), which will contribute to their abilities and motivation. Therefore, the purpose of this study was to adapt and test a program for providing entering college students training in the use of learning strategies designed to increase their achievement levels as evidenced by (a) academic performance during their first four terms, (b) retention after their first year, and (c) graduation rate.

The intervention presented in this research was designed to provide entering college students with specific instruction that, by virtue of its content and method of delivery, would enhance their desire and ability to succeed academically and make educational progress. Explicit instruction in learning strategies represents a potentially promising approach for increasing academic success as manifested by grade point average (GPA), retention, and graduation rate.

Learning strategies are essential to being successful in college. That academic tasks at the college level tend to demand a far higher level of thinking and independent learning than those encountered in secondary school (Mackenzie, 2009) underscores the importance of learning strategies. A relevant general approach to teaching learning strategies, labeled *learning to learn*, has its basis in cognitive psychology and its emphasis on self-regulated and strategic learning (Bembenutty, 2008). Self-efficacy and effective time management, key aspects of self-regulated learning, are predictors of success in college academics (Kitsantas, Winsler, & Huie, 2008). Furthermore, students' academic competence depends on the knowledge of how to use effective study strategies (Gettinger & Seibert, 2002). The works of Forster, Swallow, Fodor, and Foulser (1999), Hofer and Yu (2003), Burchard and Swerdzewski (2009), and Nordell (2009) have illustrated the effect of study strategies instruction on academic performance, while the model described in this study features an integrated and focused approach, using a set of specific strategies and substrategies that can be applied to a variety of learning tasks.

RELATED RESEARCH

Learning Skills Interventions

Hattie, Biggs, and Purdie (1996, p. 99) described a learning skills intervention as an innovation that is "aimed at enhancing motivation, mnemonic skills, self-regulation, study-related skills such as time management, and even general ability itself; creating positive attitudes toward both content and context; and minimizing learning pathologies." They classified the interventions as *cognitive* (e.g., developing a particular skill such as notetaking), *metacognitive* (e.g., focusing on self-regulation and the management of learning), and *affective* (e.g., focusing on motivation, self-concept, locus of control, and attributions). They reported a disparity between research results and the actual use of interventions as reflected by the widespread use of study skills courses with fairly limited supportive research.

Research focused on the instruction of a particular skill, such as notetaking, and the implementation of that skill, have produced positive results (Henk & Stahl, 1985). Research results were also more positive when the interventions included cognitive and metacognitive domains and were related to the content of specific courses rather than as isolated, generalizable skills (Garner, 1990). Better yet was the three-component model (cognitive, metacognitive, affective) that provided an impetus for the development of study strategies, supported by the development of self-regulating skills (Hattie et al., 1996). A persisting problem, however, has been that students outside the situation in which the strategies are presented do not apply or transfer them to new situations (Garner, 1990; Pintrich & de Groot, 1990). Yet, motivational beliefs and learning strategies have been found to have a significant effect on student learning, with females shown to exceed males in using rehearsal, elaboration, organization, and metacognitive processing (Lynch, 2008).

In their meta-analysis of research on interventions, Hattie et al. (1996) concluded that learning strategies instruction is most effective when applied in the context of real academic needs and goals, such as provided in a content course, rather than in a counseling or remedial center. Two study tactics found to be effective at the postsecondary level are self-questioning (i.e., generating questions about what is to be learned) and concept mapping, a procedure for the graphic organization of information (Bernard & Naidu, 1992; Briscoe & LaMaster, 1991). Nisbet and Adesope (2006), in a meta-analysis, found that students ranging from high school to postsecondary grades used concept maps to learn in a variety of domains (e.g., science and psychology), and that the use of concept maps was associated with increased knowledge retention.

There is also evidence that shows how the use of technology was related to learning (Schmid et al., 2009). First, the use of technology was limited regarding affecting learning achievement. Second, using technologies to support cognition yielded better results than using it to present or deliver content. That is, applications that supported thinking and doing yielded better results than did applications related to receiving and internalizing content. Third, low or moderate technology saturation led to larger effects than did more highly saturated classroom uses, suggesting that technologies themselves can impose—rather than reduce—cognitive load, causing a reduction in performance.

Overall, research on the effects of learning strategies courses as an intervention are considered by some as lacking rigor and, in particular, lacking published evaluations and external measures of success (e.g., GPA and retention; Hadwin & Winne, 1996) and using self-reported measures instead (Petrie, 1998). There were, however, a small number of studies that applied some external measures indicating that participating in a study strategies course had a positive effect, especially among at-risk learners (Forster, Swallow, Fodor, & Foulser, 1999).

Online/Computer-Enhanced (Hybrid) Course Outcomes

Many higher education institutions are turning to hybrid and online courses as an instructional format. Understanding the students' experiences in these courses has implications for the effectiveness of teaching strategies. In a study of students' positive and negative experiences in hybrid and online classes by El Mansour (2007), it was found that flexibility in the class schedule and the instructor's availability were positive experiences for students and problems with technology were negative ones. One way to deal with many technology problems is to use a hybrid format balancing traditional face-to-face classroom instruction with online components (Jackson & Helms, 2008) as illustrated by the approach used in this study. However, it is important to make sure that the students receive the necessary support to complete the online components in order for the approach to be successful.

Another example of the hybrid part online/part face-to-face approach was provided by Riffell and Sibley (2005) in an introductory biology course for non–science majors. The hybrid course included weekly online assignments and weekly meetings focused on active learning exercises. The hybrid course was taught with a traditional course for comparison purposes. Students in the hybrid course reported higher quality of interaction with the instructor, more use of the text, and more frequent study groups than students taught the traditional way. Online assignments were equivalent to or better than passive lectures, and active exercises were more effective when combined with online activities. The advantages of Web-based technologies and the best ways for students to use them have been documented by Barcelona (2009).

Given the magnitude of the retention problem, learning strategies interventions and the use of online, computer-enhanced (hybrid) methods of instruction may have the potential to help students succeed in higher education. As student populations increase in number and diversity, it is important to discover more effective ways to enhance academic achievement. The purpose of this study is to evaluate the effect of an innovative approach to teaching learning strategies to students using a computer-enhanced (hybrid) instructional design.

Research on Other Study Skills Courses

For comparison purposes, we examined three other study strategies courses: “Teaching Self-Regulated Learning Through a Learning-to-Learn Course” (Hofer & Yu, 2003), “Effects of a College Study Skills Course on At-Risk, First-Year Students” (Forster et al., 1999), and “Evaluation of an Academic Study Skills Course” (Petrie, 1998). The intent was to determine the characteristics of courses that had been the subject of previous research, as well as identify which success factors had been analyzed. This enabled us to compare our approach for teaching learning strategies to those used by other researchers.

All three of the other approaches differed considerably from ours in three important aspects: (a) sample size, (b) use of comparison groups, and most important, (c) reliance on self-report data. Whereas the sample size for our study was 702, the sample sizes for the three comparison study skills courses were 78, 143, and 415, respectively. While our course evaluation used closely matched non–course takers as a comparison group in a quasi-experimental design, the three comparison study skills courses used pretests and posttests, but no comparison groups. Last, and most important, whereas our course evaluation used GPA gains, increase in retention, and increase in graduation rate as outcome criteria, all three of the comparison study strategies courses used self-report data on a variety of questionnaires (e.g., the Motivated Strategies for Learning Questionnaire, the Learning and Study Strategies Inventory, and the Cognitive Skills Inventory).

THE STRATEGIES FOR ACHIEVEMENT APPROACH

The learning strategies program examined in this study evolved from the achievement motivation model for entrepreneurship originally espoused by David McClelland (1979), but the inclusion of more current social-cognitive and schema theories based on considerable research and testing has translated the model into strategies for success in education (Tuckman, 2002, 2003; Tuckman, Abry, & Smith, 2008). The strategies and substrategies, summarized in Table 1, focus on enhancing self-regulation and strategic learning and influence how students approach, carry out and evaluate a learning task. Paris and Newman (1990), Zimmerman (2000), and Schunk (2001) have highlighted the importance of self-regulation in successful learning.

TABLE 1
Strategies and Substrategies in the Strategies-for-Achievement Approach

Strategy	*Substrategy*
Take reasonable risk	• Set goals • Break tasks down into bite-sized pieces
Take responsibility for your outcomes	• Focus your thoughts on self and effort as causal explanations • Plan
Search the environment for information	• Ask questions • Use visualization
Use feedback	• Self-monitor • Self-instruct

Supporting this approach is a conceptual framework for self-regulation directly addressing the issue of increasing student achievement in school. The framework includes a motivational and cognitive component, as well as two sources of influence: (a) knowledge and beliefs and (b) strategies (Garcia & Pintrich, 1994). In this framework, the aforementioned strategies and substrategies are used as the basis for a program aimed at teaching students to meet the goals of overcoming procrastination, building self-confidence, becoming more responsible, managing their lives, learning from lecture, learning from text, preparing for tests, writing papers, and managing their lives.

The learning strategies approach places particular emphasis on the basic premise of social cognitive theory that there exists a mutually interactive relation among thoughts, behaviors, and environmental consequences, necessitating a change in thoughts as a prerequisite to changing behavior (Bandura, 1997). For example, in the module on procrastination, one of the 10 modules or topics that make up the course, students learn to (a) distinguish between rationalizations for procrastination (e.g., "I work better under pressure") and real reasons (e.g., self-doubt); (b) recognize the thoughts (e.g., "math confuses me"), feelings (e.g., fear) and behaviors (e.g., skipping class) that are provoked by potentially difficult situations (e.g., an impending math midterm); (c) overcome the tendency to procrastinate by using the four major strategies for achievement previously described; and (d) effectively manage their time by creating a specially designed "to-do checklist," a self-regulatory procedure that facilitates planning (Tuckman, 1992; Tuckman et al., 2008) and incorporates the first learning strategy, *take reasonable risk*, and its two substrategies, "go for goal" and "bite-sized pieces."

In the module on building self-confidence, students receive instruction on the following four techniques: (a) regulating your emotional level, (b) seeking affirmation, (c) picking the right models, and (d) "just doing it." The intention of these techniques is to create the thoughts required for successful achievement (Bandura, 1997).

In teaching students to use the *take responsibility* strategy, the approach uses causal explanations and their properties, such as those described in attribution theory (Weiner, 1986, 1995), to show students the importance of focusing on effort as the explanation for their outcomes. Perceptions of the *intentionality* of others' actions, based on causal explanations, are important factors of taking responsibility that training can modify (Graham, 1997).

The third learning strategy, *search the environment*, plays a prominent role in the domain of cognition. For example, Pressley and Wooloshyn (1995) and Mayer (2002) have described techniques for teaching students to use cognitive strategies to acquire and process information, and Mayer (1989) has shown the value of conceptual models for visualizing ways of solving problems. Robinson (1961) and Mayer (1984) relied extensively on the question-asking approach in teaching students to extract meaning from text; and Rosenshine, Meister, and Chapman (1996) reported a meta-analysis showing that teaching students to generate questions resulted in gains in comprehension. Other work has also focused on enhancing students' capability to learn from text by using outlining (e.g., Tuckman, 1993).

Zimmerman and Martinez-Pons (1986) referred to "seeking information" (p. 618), but *search the environment* has a somewhat broader meaning, one that focuses on question asking as a generic form of information processing. For example, students learn to view information that is either heard in lectures or read in text as answers to implicit questions. By making those questions explicit through the construction of a "Q&A Outline" (Tuckman et al., 2008, p. 116), students learn both to schematize the information and to organize it into visual forms such as diagrams and charts. The outlines and diagrams then help students organize and store their thoughts in long-term memory when preparing for and taking tests, as well as when writing papers. Sahari, Tuckman, and Fletcher (1996) found that students who received training on writing outlines designed to help them schematize and organize text material demonstrated significantly greater improvement on reading comprehension tests than students not similarly trained.

The fourth learning strategy, *use feedback*, has traditionally focused on external or outcome feedback (Butler & Winne, 1995), which, in general, results in performance improvement (Kulhavy, 1977; Kulik & Kulik, 1988). *Internal feedback*, consisting of learner judgment decisions regarding task success relative to multifaceted goals, and productivity of learning strategies relative to expected progress, has received more recent emphasis (Butler & Winne, 1995). *Formative feedback*, defined as information designed to improve a learner's thinking or behavior, works best when it is nonevaluative, supportive, timely, and specific (Shute, 2008). In general, feedback can be a powerful influence on learning and achievement, both in a positive and negative way. Hattie and Timperly (2007) reported that "feedback is more effective when it provides information on correct rather than incorrect responses, and when goals are specific and challenging but task complexity is low" (p. 85). Successful feedback provides students with information relative to performance goals, that is, how well they are doing and what to do next.

The *use feedback* strategy subsumes the self-regulating areas of self-monitoring, keeping records, self-evaluation, and self-consequences (Zimmerman, 1998, 2000). Carver and Scheier (1990) and Butler and Winne (1995) saw monitoring or the acquisition and use of feedback as the hub of self-regulated cognitive engagement, whereas Hadwin and Winne (1996, p. 705) cited monitoring as an approach that "modestly" enhances student achievement.

In summary, the theoretical basis for improving the academic achievement of students is to train them in the use of learning strategies, or what are referred to as *Strategies-for-Achievement*. Part of the emphasis is on teaching self-regulation in the form of taking reasonable risk through goal setting and learning in increments, as Bandura (1997) and Zimmerman's (1998, 2000) work emphasized, and on taking responsibility through the attribution of causes to changeable and controllable factors, as Weiner (1986, 1995) described. The other part of the emphasis is on teaching information processing, as Mayer (1989, 2002) and Robinson (1961) described, through the use of question asking and conceptual and visual models of problem solving (searching the environment) and using feedback, especially internal feedback, through self-monitoring, self-evaluation, and self-consequating, as Zimmerman (1998, 2000) described.

RESEARCH QUESTIONS

In this research we posed three questions:

1. Would students taking and completing the learning strategies course in their first academic term earn higher GPAs in each of the four terms during and after taking the course than a closely matched group of students who did not take the course in any of their first four terms?
2. Would first-term course takers be more likely to return to college the following year than their non–course-taking counterparts?
3. Would first-term course takers have a higher graduation rate than matched non–course takers? This design is a particular strength of our work, given that Hadwin and Winne (1996) reported fewer than 3% of the 500+ articles published about learning strategies "compared students taught a study tactic to other students who studied by whatever methods they might have developed on their own" (p. 711).

METHOD

Materials and Procedure

Instead of instruction in a traditional class setting, the learning strategies program was taught using an online, computer-enhanced (hybrid) instructional model called Active Discovery And Participation thru Technology (Tuckman, 2002). This model for teaching a Web-based course in a campus-based computer classroom combines several critical features of traditional classroom instruction: (a) required student attendance, (b) presence of a live instructor, (c) accompaniment of a printed textbook: *Learning and Motivation Strategies: Your Guide to Success* (2nd ed.; Tuckman et al., 2008), with several features of computer-enhanced instruction: (a) class time spent doing computer-mediated activities rather than listening to lectures, (b) a large number of performance activities rather than just two or three exams, (c) self-pacing with milestones rather than a lockstep pattern. The program included more than 200 learning/performance activities that were the same across all cohorts. These activities ranged from assignments that required students to perform specific skills incorporating the learning strategies, such as giving an example of how to think positively, portfolios that required students to write short essays on a topic or provide examples of how topics could be applied to solve a problem, postings on an online, asynchronous discussion board, and quizzes on content topics, all of which students submitted electronically and instructors graded.

To provide additional opportunities for students to use learning strategies, they were required to read *A Hope in the Unseen* (Suskind, 1998), a biography of Cedric Jennings—a young African American student—that described his last year in an urban high school and first year in an Ivy League college. While reading the book, students wrote and submitted four 2-page papers that analyzed Cedric's actions and experiences, using the four learning strategies and eight substrategies. Reading the book and writing the papers helped students become more familiar with the strategies and substrategies as well as improve their reading and writing skills. As in all of these activities, their instructors gave students feedback.

Participants and Matching Procedure

The population of concern in this study was first-term students attending a large Midwestern university. The procedure used in the method of matching focused specifically on meeting the criteria specified by Hadwin and Winne (1996) such that its goal was to be able to compare students taking the learning and strategies course to those "who studied by whatever methods they might have developed on their own" (Hadwin & Winne, 1996, p. 711) and thus more reasonably attribute any differences between these groups to the influence of the course. The matching procedure we chose was necessary because students enrolled in the learning and strategies course voluntarily, often on the suggestion of an academic advisor. Matching on these variables was done to help attenuate the potential difficulties in the interpretation of group differences resulting from a self-selection bias.

In particular, we looked at the records of 351 students enrolled in the learning strategies course (course takers) during their first term at the university in addition to 351 matched control students (non–course takers) matched according to term of enrollment, gender, ethnicity, age, high school class rank, and ACT composite or SAT verbal/math composite (ACT). The student records used for this study covered a total of seven autumn term cohorts ranging from Fall 2000 through Fall 2006.

Because the majority of students had ACT composite scores and only a relatively small number of students had SAT verbal/math scores, we converted SAT verbal/math composite scores into ACT composite scores using a standard concordance table (ACT, Inc, 2010, http://www.act.org/aap/concordance; see Table 1). In all cases where students had taken a test more than once or had both an ACT composite and SAT verbal/math score, we used the highest score.

Our use of high school class rank as a matching variable and, as subsequently described, a covariate in our model may appear to be problematic because high school class rank has the potential problem of incommensurability in that a student attending one high school could have a different rank placement at a different high school. Despite this incommensurability, high school class rank is one of the variables used in the selective admissions process and, although not significantly related to graduation status, is significantly correlated with academic achievement ($r = .25$ with first-year cumulative GPA). It was expected that excluding this variable as a matching variable and a covariate in our model would have seriously confounded the interpretations of our comparisons of the groups, in particular for the GPA measure.

Although the intent of the matching procedure was to match students by group such that there were no main effects of any of the matching variables, it was possible to find a one-to-one matched-control student only by term of enrollment, gender, and ethnicity for each course taker. Thus, every course taker from a given cohort year, gender, and ethnic group, was matched to a non–course taker from the same cohort year, gender, and ethnic group.

However, it was not possible to find one-to-one matches for class rank, ACT, and age. For class rank, the study matched course takers to non–course takers according to class rank decile clusters. For ACT, the study used seven clusters: (a) less than 18, (b) 18 through 23, (c) 24 and 25, (d) 26 and 27, (e) 28 through 30, (f) 31 through 33, and (g) greater than or equal to 34. In particular, for every course taker, a number of non–course takers of the same gender and ethnicity entering the university during the same term were generally available and thus selected as potential candidates for matching. From this list, a reduced number of matched control non–course takers were selected when those students' class rank and ACT scores fell within the same cluster range as the course taker. Last, from this reduced list, one matched non–course taker control student was selected based on similarity of age. Every attempt was made to match students on age within four age clusters: (a) less than 18 years of age, (b) 18–19 years of age, (c) 20–22 years of age, and (d) greater than 22 years of age.

Thus, in summary, the matching protocol specified that every course taker was matched exactly to a non–course taker on the basis of entering term, gender, and ethnicity. Once this was accomplished, students were matched according to ability (class rank and ACT), and then on age.

Statistical Analyses

Of primary concern in this study was the assessment of potential differences between course takers (GROUP = 1) and non–course takers (GROUP = 0) on term GPA (TGPA, on a scale of 0.00 to 4.00) and retention status (STATUS) over the course of their first four terms (excluding summer). In addition, there was also interest in assessing whether there were differences in 4-, 5-, and 6-year graduation rates between the groups for the Fall 2000, 2001, and 2002 cohorts.

To study group differences in TGPA and STATUS, we built three-level hierarchical linear models (Raudenbush & Bryk, 2002) to assess potential overall mean level differences and the potential moderation of changes over time, by group. Thus, time (term of enrollment or TERM) is the Level 1 variable and includes the first four terms of enrollment. In particular, these terms include students' first autumn (AU1 = 0), winter (WI1 = 1), and spring terms (SP1 = 2), as well as the fall term of the second year (AU2 = 3). Coding AU1 as zero allows for the interpretation of initial status as performance or retention during the first term of enrollment. In calculating GPAs for course takers at the end of the first term, the study did not include the learning strategies course grade.

TERM is nested within student (Level 2), which is nested within cohort (Level 3). Even though there were only seven cohorts at Level 3, differences among the cohorts with respect to prior ability seemed to necessitate the inclusion of this level to assess the proportion of variance in TGPA accounted for on the basis of when students entered the university. Because of changes in policy regarding selective admissions, which included a focused attempt on gradually increasing the overall mean level of standardized test scores and high school class rank of incoming first-term students, ACT and class rank tended to increase over the 7 years included in this study. Thus, this study included ACT and class rank (group mean centered) as covariates in the conditional models in order to control for prior ability.

The conditional model for analyzing TGPA was $TGPA = \pi_0 + \pi_1(TERM) + e$ where $\pi_0 = \beta_{00} + \beta_{01}(GROUP) + \beta_{02}(CR) + \beta_{03}(ACT) + r_0$ and $\pi_1 = \beta_{10} + \beta_{11}(GROUP) + \beta_{12}(CR) + \beta_{13}(ACT) + r_1$, where CR is class rank. Thus, the estimated parameters used to assess the relation between TERM and TGPA are random functions of GROUP, class rank, and ACT with the random components denoted as r_0 and r_1. Furthermore, the beta weights (β) include a fixed-effect component (γ) and a random-effects component (u), although the inclusion of this latter component depends on the extent of the variability of β. While we expected that cohort variability would influence the GROUP, class rank, and ACT effects on overall TGPA mean level as well as their interaction with TERM, an initial analysis including this variability revealed that only the intercepts of TGPA initial status (i.e., first term of enrollment) and the TERM rate (i.e., $\tau_{\beta 00}$ and $\tau_{\beta 10}$) were statistically significant. As such, the cohort random effects only include $\tau_{\beta 00}$ and $\tau_{\beta 10}$ (i.e., $\beta_{00} = \gamma_{000} + u_{00}$ and $\beta_{10} = \gamma_{100} + u_{10}$). Beta weights assessing mean or initial status differences (i.e., β_{01}, β_{02}, and β_{03}) and rate or interaction effects (i.e., β_{11}, β_{12}, and β_{13}) were fixed effects only (i.e., only gamma weights are estimated). Of particular interest are $\beta_{01} = \gamma_{010}$ and $\beta_{11} = \gamma_{110}$, with γ_{010} assessing the overall mean level or initial status differences between course takers and non–course takers and γ_{110} assessing differences between the groups in changes in TGPA over time (TERM).

In analyzing STATUS, a logit link function linked retention probability to the parameter estimates. Specifically, $P(STATUS = 1|\pi\ ) = \varphi$, where $log(\varphi/(1 - \varphi) = \eta$ and $\eta = \pi_0 + \pi_1(TERM)$. Thus, STATUS is a Bernoulli random variable with STATUS = 1 indicating retention and STATUS = 0 indicating attrition for a given term of enrollment. The parameters (π_0 and π_1) have the same linear structure as those used in analyzing TGPA, with the exception that π_0 and β_{00} have no random components. All other beta weights represent fixed effects only. The hierarchical linear model analyses of TGPA and STATUS used HLM 6.06 (Raudenbush, Bryk, & Congdon, 2008).

To study graduation rate differences (GRAD) between the groups, a logistic analysis included ACT, class rank, and first-term GPA (academic standing) dichotomized into (a) students in academic difficulty (i.e., GPA <2.00) and (b) students in good academic standing (i.e., GPA ≥ 2.00).

Last, effect sizes for the analysis of TGPA are in the r metric where $r = [t^2/(t^2 + df)]^{1/2}$ (Rosenthal, 1994). Effect sizes for the analyses of retention rates are odds ratios (θ; Fleiss, 1994). Effect sizes for chi-squares tests of variability and graduation rates are Cramer's $\phi' = [\chi^2/(Ndf)]^{1/2}$ (Cohen, 1988).

RESULTS

Comparisons of Course Takers to Non–Course Takers With Respect to Matching Variables

Overall, the sample of 702 students included 45.9% women, 79.5% White, 13.4% African American, 3.1% Asian/Pacific Islander, 2.3% Hispanic, 0.3% Native

TABLE 2
Distributions of Cohort Year, Gender, and Ethnicity for Course Takers and Non–Course Takers Combined

	Ethnicity							
	Minority		*White*		*Unknown*			
Cohort year	n	%	n	%	n	%	*Total*	*Sample (%)*
AU00	2	50.0	2	50.0	0	0.0	4	
	8	80.0	2	20.0	0	0.0	10	
Cohort total	10	71.4	4	28.6	0	0.0	14	2.0
AU01	14	20.6	54	79.4	0	0.0	68	
	16	36.4	28	63.6	0	0.0	44	
Cohort total	30	26.8	82	73.2	0	0.0	112	16.0
AU02	16	21.6	58	78.4	0	0.0	74	
	20	25.0	60	75.0	0	0.0	80	
Cohort total	36	23.4	118	76.6	0	0.0	154	21.9
AU03	14	17.9	62	79.5	2	2.6	78	
	12	17.1	58	82.9	0	0.0	70	
Cohort total	26	17.6	120	81.1	2	1.4	148	21.1
AU04	4	7.4	50	92.6	0	0.0	54	
	4	8.7	42	91.3	0	0.0	46	
Cohort total	8	8.0	92	92.0	0	0.0	100	14.2
AU05	4	5.4	66	89.2	4	5.4	74	
	12	18.8	50	78.1	2	3.1	64	
Cohort total	16	11.6	116	84.1	6	4.3	138	19.7
AU06	4	14.3	22	78.6	2	7.1	28	
	4	50.0	4	50.0	0	0.0	8	
Cohort total	8	22.2	26	72.2	2	5.6	36	5.1
Grand total	134	19.1	558	79.5	10	1.4	702	

American, and 1.4% unknown. Table 2 shows the distributions of cohort year and ethnicity for course takers and non–course takers. The distributions of the two groups are combined because they are identical with respect to cohort year, gender, and ethnic group. The minority column in Table 2 includes all ethnic groups except White and unknown.

Although 30 (8.5%) course takers were not matched exactly according to clustering criterion for ACT and 7 (2.0%) course takers were not matched according to the class rank clustering criterion, the two groups have ability distributions that are virtually identical (see Table 3). Chi-square goodness of fit tests for class rank ($\chi^2 = 0.40$, $df = 8$, $p = .999$, $\phi' = .01$) and ACT ($\chi^2 = 2.54$, $df = 5$, $p = .770$, $\phi' = .03$) also suggest that two groups did not differ significantly with respect to these variables. The 95% CIs for the mean class rank were [66.58, 70.63] and [67.27, 71.32] for course takers and non–course takers, respectively. There was also considerable overlap between the groups for the standard deviation of class

TABLE 3
Point and Interval Estimates for Mean, Standard Deviation, and Median, by Group and Cohort

	Non–Course takers						*Course takers*					
Cohort	*M*	*95% CI*	*SD*	*95% CI*	*Median*	*95% CI*	*M*	*95% CI*	*SD*	*95% CI*	*Median*	*95% CI*
Age												
AU00	18.00	[18.00, 18.00]	0.00	N/A	18.00	[18.00, 18.00]	18.57	[17.17, 19.97]	1.51	[0.97, 3.29]	18.00	[18.00, 19.07]
AU01	17.93	[17.82, 18.04]	0.42	[0.34, 0.52]	18.00	[18.00, 18.00]	18.00	[17.88, 18.13]	0.47	[0.39, 0.57]	18.00	[18.00, 18.00]
AU02	18.13	[18.04, 18.22]	0.38	[0.32, 0.45]	18.00	[18.00, 18.00]	18.16	[18.07, 18.24]	0.37	[0.32, 0.43]	18.00	[18.00, 18.00]
AU03	18.16	[18.08, 18.24]	0.37	[0.32, 0.44]	18.00	[18.00, 18.00]	18.22	[18.09, 18.34]	0.53	[0.45, 0.63]	18.00	[18.00, 18.00]
AU04	18.58	[18.15, 19.01]	1.50	[1.25, 1.87]	18.00	[18.00, 18.00]	18.18	[18.06, 18.30]	0.44	[0.37, 0.55]	18.00	[18.00, 18.00]
AU05	18.20	[18.08, 18.33]	0.53	[0.46, 0.64]	18.00	[18.00, 18.00]	18.19	[18.09, 18.29]	0.43	[0.37, 0.52]	18.00	[18.00, 18.00]
AU06	18.17	[17.98, 18.36]	0.38	[0.29, 0.58]	18.00	[18.00, 18.00]	18.06	[17.94, 18.17]	0.24	[0.18, 0.35]	18.00	[18.00, 18.00]
Total	18.18	[18.11, 18.26]	0.71	[0.66, 0.76]	18.00	[18.00, 18.00]	18.16	[18.11, 18.21]	0.49	[0.45, 0.52]	18.00	[18.00, 18.00]
ACT composite scores												
AU00	19.71	[17.67, 21.76]	2.22	[1.43, 4.88]	19.00	[18.20, 21.53]	19.57	[17.73, 21.41]	1.99	[1.28, 4.38]	19.00	[18.20, 21.27]
AU01	23.80	[23.07, 24.54]	2.74	[2.32, 3.38]	24.50	[23.00, 25.00]	23.82	[23.04, 24.60]	2.92	[2.47, 3.59]	24.00	[23.00, 25.00]
AU02	22.90	[22.13, 23.66]	3.37	[2.91, 4.01]	23.00	[22.46, 24.00]	22.48	[21.68, 23.29]	3.55	[3.06, 4.21]	23.00	[22.00, 23.00]
AU03	23.11	[22.37, 23.85]	3.19	[2.74, 3.80]	23.00	[22.00, 24.00]	22.99	[22.24, 23.74]	3.23	[2.78, 3.86]	23.00	[22.00, 24.00]
AU04	26.16	[25.26, 27.06]	3.18	[2.65, 3.96]	27.00	[25.00, 27.33]	24.58	[23.73, 25.43]	2.98	[2.49, 3.71]	25.00	[24.00, 26.00]
AU05	24.52	[23.84, 25.21]	2.85	[2.44, 3.42]	25.00	[24.00, 26.00]	24.29	[23.60, 24.98]	2.89	[2.48, 3.47]	24.00	[23.89, 25.11]
AU06	24.17	[22.24, 26.10]	3.88	[2.92, 5.82]	24.00	[21.00, 27.00]	24.22	[22.13, 26.32]	4.21	[3.16, 6.31]	24.00	[21.52, 27.00]
Total	23.87	[23.52, 24.22]	3.33	[3.10, 3.60]	24.00	[24.00, 24.00]	23.49	[23.14, 23.85]	3.31	[3.08, 3.58]	24.00	[23.00, 24.00]
High school class rank												
AU00	70.44	[53.56, 87.32]	18.25	[11.76, 40.19]	74.00	[59.64, 81.29]	70.96	[54.85, 87.06]	17.41	[11.22, 38.34]	71.50	[58.13, 84.65]
AU01	55.08	[49.46, 60.70]	21.00	[17.70, 28.80]	55.15	[46.60, 63.80]	55.18	[49.33, 61.02]	21.83	[18.40, 26.83]	55.33	[46.98, 65.17]
AU02	70.26	[66.04, 74.49]	18.62	[16.08, 22.14]	75.60	[65.87, 79.00]	70.00	[65.64, 74.37]	19.22	[16.59, 22.85]	73.60	[69.69, 79.29]
AU03	68.15	[63.95, 72.36]	18.15	[15.63, 21.66]	71.00	[66.10, 77.19]	67.99	[63.88, 72.10]	17.74	[15.27, 21.17]	70.50	[66.26, 76.27]
AU04	77.86	[73.24, 82.47]	16.24	[13.56, 20.23]	80.05	[76.64, 85.83]	74.80	[70.46, 79.13]	15.26	[12.75, 19.01]	76.00	[69.50, 83.20]
AU05	75.78	[72.36, 79.20]	14.23	[12.19, 17.10]	75.70	[73.02, 80.70]	74.62	[70.88, 78.36]	15.58	[13.34, 18.72]	75.90	[73.41, 80.22]
AU06	64.97	[54.12, 75.81]	21.81	[16.36, 32.69]	66.95	[50.45, 83.08]	65.72	[54.54, 76.89]	22.47	[16.86, 33.69]	66.90	[52.03, 82.77]
Total	69.29	[67.27, 71.32]	19.26	[17.93, 20.80]	72.90	[69.77, 75.76]	68.60	[66.58, 70.63]	19.31	[17.98, 20.84]	72.20	[69.50, 74.90]

rank. In particular, the 95% CIs for the standard deviation were [17.98, 20.84] and [17.93, 20.80] for course takers and non–course takers, respectively. The results for ACT composite were similar: the mean 95% CIs were [23.14, 23.85] and [23.52, 24.22], and the standard deviation 95% CIs were [3.08, 3.58] and [3.10, 3.60] for course takers and non–course takers, respectively. The distribution of the paired differences scores of ACT and class rank was highly leptokurtic (kurtosis = 21.7 and 22.2 for ACT and class rank, respectively) and negatively skewed (skewness = −2.8, and −3.5 for ACT and class rank, respectively). Again, the severe leptokurtosis exists because the course takers were successfully matched to non–course takers. The negative skew is the result of the few outliers that were not well matched because of the clustering constraints. The 95% CI for the mean of the paired difference scores for ACT and CR was [−0.61, −0.16] and [−1.48, 0.10], respectively. While this suggests that students may have differed slightly with respect to the mean ACT, it must be pointed out that 94.5% of non–course takers had ACT scores within ±3 ACT points of course takers. In addition, 98.0% of non–course takers had CR scores with plus or minus 1 decile of course takers. Point estimates and 95% CIs of ACT and CR for each group by cohort are provided in Table 3 which shows that the two distributions of these variables for course takers and non–course takers are very similar.

There were 7 course takers (2.0%) who were unable to be matched according to the clustering criterion for age. Nevertheless, the two groups were similar according to age ($M = 18.16$, $SD = 0.49$, for course takers; $M = 18.18$, $SD = 0.71$, for non–course takers). The percentage of 18-year-olds for course takers and non–course takers was 80.6% and 80.3%, respectively. The percentage of students older than 18 years old was 16.8% and 16.2% for course takers and non–course takers, respectively. A small proportion of the sample (2.6% of course takers and 3.4% of non–course takers) was younger than 18 years old. Thus, the distribution of the paired difference scores between course takers and non–course takers was highly leptokurtic (kurtosis = 32.2) and negatively skewed (skewness = −3.6). The severe leptokurtosis exists because most of the course takers were successfully matched to non–course takers. The negative skew is the result of a few outliers that were not well matched because of the clustering constraints for age. Nevertheless, the 95% CIs for the mean of the paired difference scores for age were [−0.13, 0.08]. Point estimates and 95% CIs of age for each group, by cohort, are provided in Table 3, which shows that the two distributions of age for course takers and non–course takers are similar. Comparing the two distributions with a chi-square goodness-of-fit test further confirms that the age distributions are similar ($\chi^2 = 4.64$, $df = 3$, $p = .200$, $\phi' = .05$).

Last, for all seven cohorts studied, the median values of CR and ACT for course takers and non–course takers were generally below the population (i.e., all first-term students) medians for these measures. As shown in Figure 1, the class rank and ACT median values for non–course takers and course takers tended to

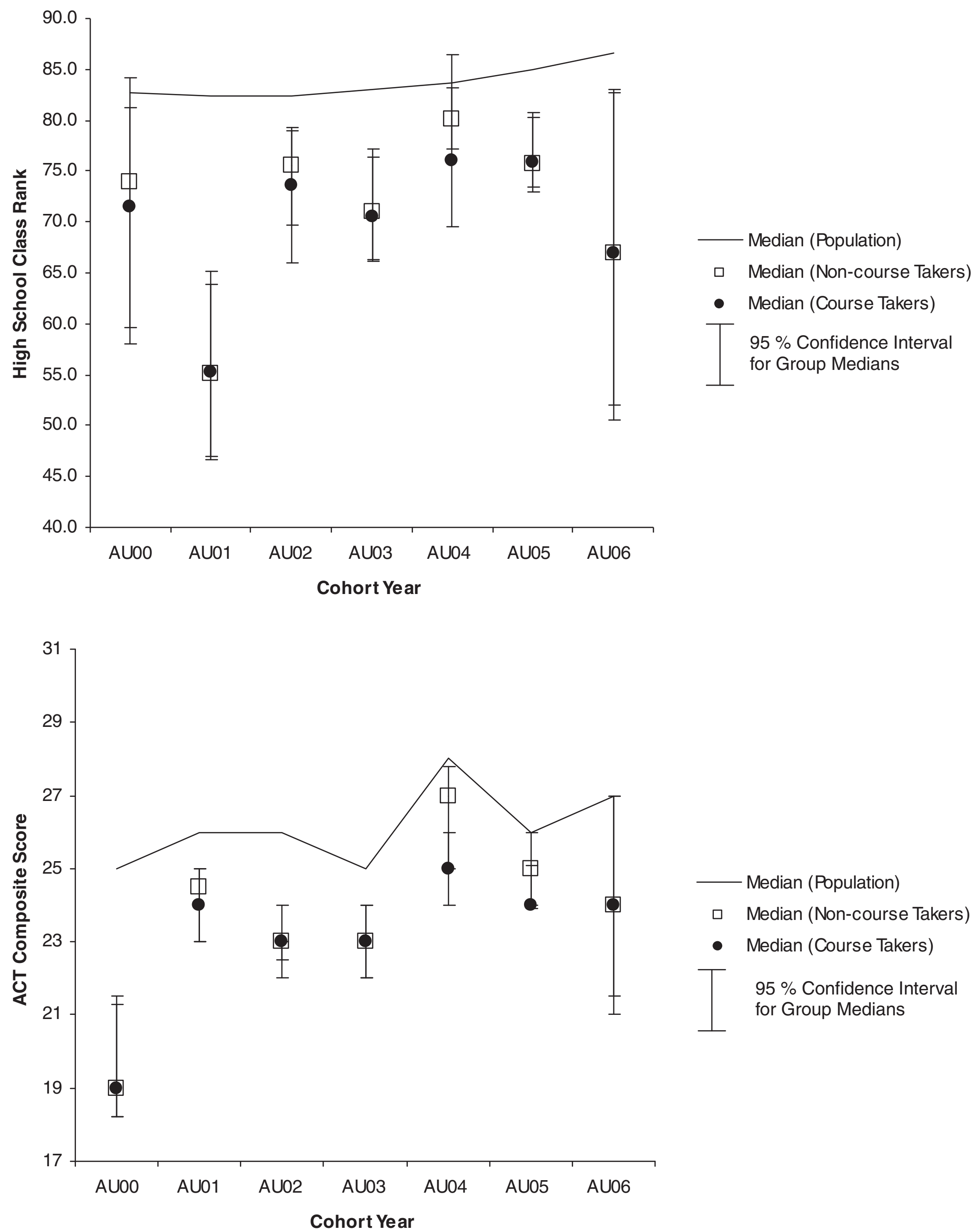

FIGURE 1 High school class rank and ACT population and group medians.

fall significantly below the population median values as indicated by the 95% CIs for the group medians. This indicates that these students were likely to be at somewhat of an academic disadvantage relative to the population of students from which they were drawn.

Comparisons of Course Takers to Non–Course Takers With Respect to Achievement Variables

TGPA

The first analysis was a three-level unconditional model. That is, both groups were combined so that the overall variability in (a) first-term TGPA and (b) rate of change in TGPA over the first four terms, as a result of cohort differences, could be examined free of covariates. In addition, the unconditional model allows for an assessment of the significance of change of TGPA over TERM. In particular, the analysis is a regression of TGPA only on TERM (i.e., $TGPA = \pi_0 + \pi_1(TERM) + e$). The intercept represents TGPA during the first term of enrollment (i.e., initial status) and the slope represents the rate of change of TGPA over the four terms studied.

There was considerable variability of the first-term TGPA ($\tau_{\pi 0} = 0.29$, $\chi^2 = 1620.88$, $df = 679$, $p < .0001$, $\phi' = .06$; $\tau_{\beta 00} = .01$, $\chi^2 = 23.44$, $df = 6$, $p = .001$, $\phi' = .08$) and rate ($\tau_{\pi 1} = 0.02$, $\chi^2 = 995.87$, $df = 679$, $p < .0001$, $\phi' = .05$; $\tau_{\beta 00} = 0.002$, $\chi^2 = 23.73$, $df = 6$, $p = .001$, $\phi' = .08$) parameters, most of which was student variability. Only 3.97% and 8.00% of the variability of first-term TGPA and rate, respectively, were the result of cohort differences. In addition, TGPA declined significantly over the first four terms of enrollment for both groups combined ($\gamma_{100} = -0.09$, $t = -4.26$, $df = 6$, $p = .006$, $r = .87$). The fixed effect for rate suggests a 3% drop in TGPA per term for all students. Last, within cohorts, the correlation between first-term TGPA and rate was $-.11$, suggesting that the decrease in TGPA over terms is somewhat attenuated as the first-term TGPA decreases. This implies that, in general, students with higher first-term TGPA tended to experience a faster rate of decline of their GPA over the four terms of this study.

There was a statistically significant group difference in overall mean level of TGPA after class rank and ACT were taken into account ($\gamma_{010} = 0.11$, $t = 2.24$, $df = 698$, $p = .026$, $r = .08$). In addition, class rank had a statistically significant positive relationship with TGPA during the first term of enrollment ($\gamma_{020} = 0.01$, $t = 6.69$, $df = 698$, $p < .0001$, $r = .25$). However, none of the covariates affected the rate of decline in TGPA over the four terms studied. This suggests that course takers tended to maintain their GPA advantage over non–course takers during their first year at the university even though their GPA was declining at the same rate. This can be seen in Table 4 and in Figure 2, which shows TGPA decline over the four terms for both groups but with a clear difference between course takers and non–course takers. The thin dotted line in Figure 2, which shows TGPA for the population of all students, suggests that the term GPA decline is a common phenomenon. Given that course takers and non–course takers were similar in ability as measured by class rank and ACT and given that they tended to have ability levels below the median of the population, these results suggest that taking the course has a statistically significant effect on overall performance.

TABLE 4
Mean Term Grade Point Averages With Standard Errors of the Mean by Group and Term of Enrollment

	Course takers		*Non–Course takers*	
Term	M	SE	M	SE
AU1	2.97	0.04	2.85	0.04
WI1	2.83	0.04	2.75	0.04
SP1	2.83	0.04	2.71	0.04
AU2	2.77	0.04	2.66	0.05

Retention Status

The experiment studied retention status as a Bernoulli random variable with STATUS = 1 indicating retention and STATUS = 0 indicating attrition for a given term of enrollment (see Table 5). Variability of the initial status parameters was not of interest in this analysis (i.e., $\pi_0 = \beta_{00} = \gamma_{000}$), because only three of the 702 students (all of whom were non–course takers) withdrew during their first term of enrollment. However, we estimated the variability of the rate parameter within and between cohorts, as we expected that within and/or between cohort variability would be statistically significant.

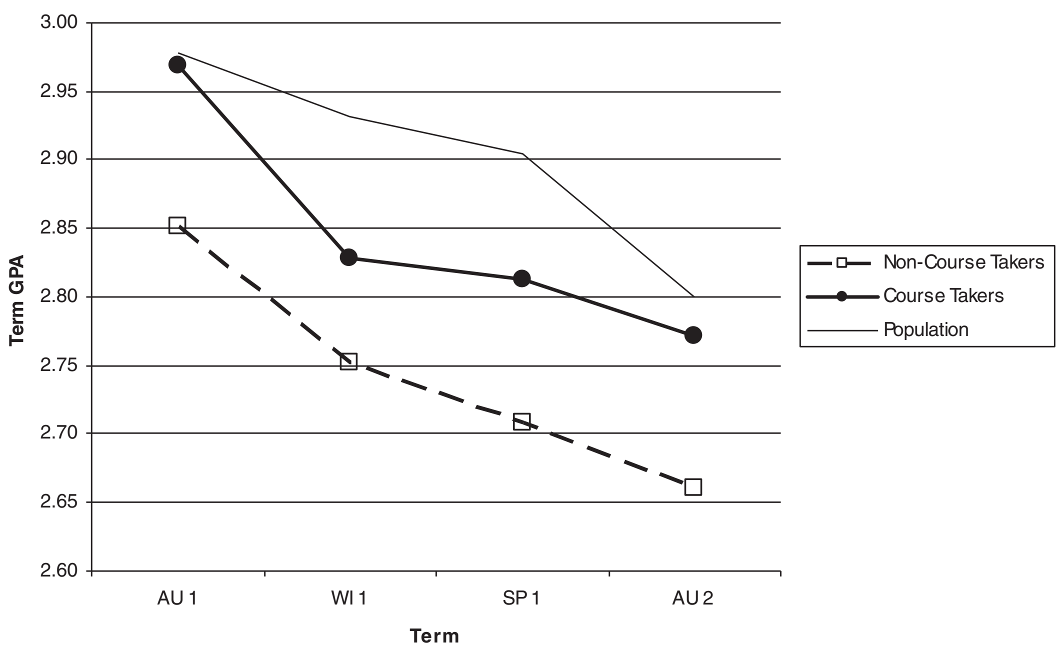

FIGURE 2 Term grade point average as a function of term of enrollment.

TABLE 5
First-Year Retention Percentages, by Group and Term of Enrollment

	Course takers			*Non–Course takers*		
Term	*Retained* (n)	*Not retained* (n)	*Retained* (%)	*Retained* (n)	*Not retained* (n)	*Retained* (%)
AU1	351	0	100.0	348	3	99.1
WI1	347	4	98.9	330	21	94.0
SP1	340	11	96.9	319	32	90.9
AU2	328	23	93.4	300	51	85.5

For the unconditional model, holding cohort constant, the predicted retention status for both groups during the first term was 98.7% ($\gamma_{000} = 4.34$, $t = 18.71$, $df = 2806$, $p < .0001$, $\theta = 76.97$). In addition, both groups had a statistically significant decrease in overall retention status over the four terms studied ($\gamma_{100} = -0.67$, $t = -5.98$, $df = 6$, $p < .0001$, $\theta = 0.51$). This suggests that on average the log-odds of being retained decreased by 0.67 for each increment in term of enrollment. Furthermore, the odds ratio associated with this decline of 0.51 suggests that on average the odds of not being retained was almost two times greater for any student in these groups at term T_{t+1} relative to term T_t. The results were similar when averaged over the entire population of cohorts. That is, not holding cohort constant, the overall retention status for both groups decreased at a statistically significant rate over the four terms studied ($\gamma_{100} = -0.82$, $t = -8.13$, $df = 6$, $p < .0001$, $\theta = 0.44$), and corresponding odds ratio of 0.44 suggests a slightly higher average rate of attrition (2.27 times) for these groups over the four terms studied. Also of interest is that while the rate parameter varied as a function of cohort ($\tau_{\beta 10} = 0.01$, $\chi^2 = 13.07$, $df = 6$, $p = .041$, $\phi' = 0.06$), the rate parameter variability within cohorts was not statistically significant ($\tau_{\pi 1} = 0.36$, $\chi^2 = 684.87$, $df = 695$, $p > .500$, $\phi' = .04$), suggesting a rather stable cohort effect.

For the conditional model predicting STATUS, after controlling for class rank and ACT, there was a statistically significant effect of GROUP on retention status across terms ($\gamma_{010} = 1.87$, $t = 3.06$, $df = 2806$, $p = .003$, $\theta = 6.49$). Overall, the expected odds of being retained for a course taker of average ability were more than six times that of a non–course taker of average ability. Thus, across all four terms of the study, course takers of average ability maintained a higher retention rate than did non–course takers. There were no statistically significant effects on retention status across terms for class rank ($\gamma_{120} = 0.004$, $t = 0.69$, $df = 698$, $p = .492$, $\theta = 1.00$) or ACT ($\gamma_{130} = -0.01$, $t = -0.26$, $df = 698$, $p = .797$, $\theta = 0.99$). In addition, the coefficient for the Group × Term interaction was not statistically significant ($\gamma_{110} = -0.30$, $t = -1.04$, $df = 6$, $p = 0.339$, $\theta = 0.74$). However, it is in the direction of a somewhat faster rate of attrition for non–course takers

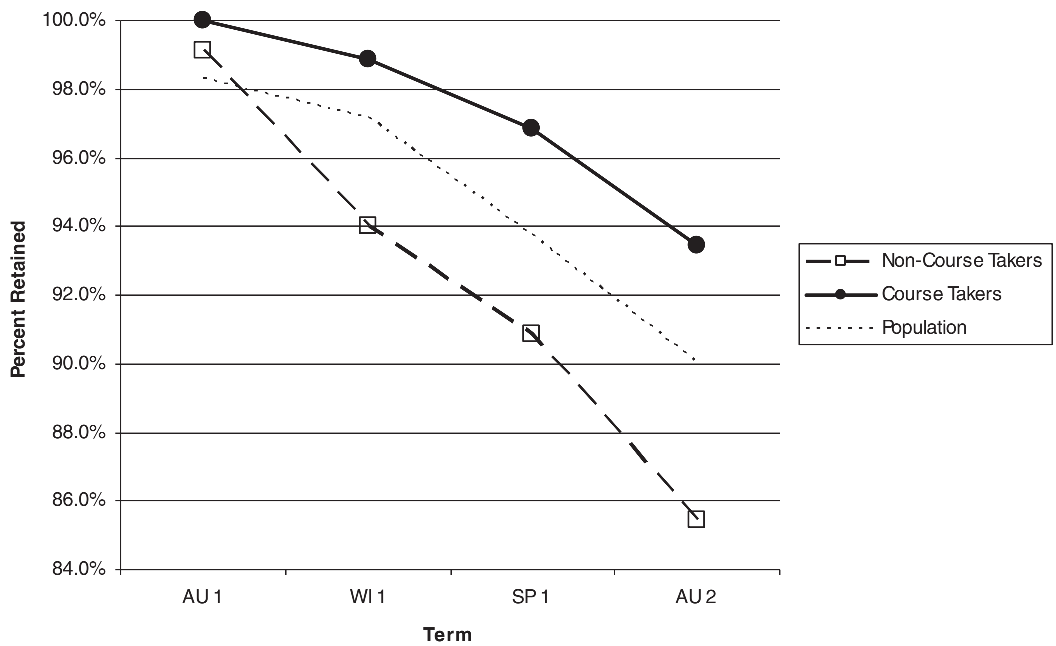

FIGURE 3 Proportion retained for each term of enrollment.

relative to course takers, as Figure 3 demonstrates. For comparison, Figure 3 also shows the population retention proportions for all students.

Graduation Rates

Controlling for academic ability and first-term GPA, graduation rate for course takers was higher overall relative to non–course takers ($\chi^2 = 10.11$, $df = 1$, $p = .002$, $\phi' = 0.12$). The odds of graduating in 4, 5, or 6 years were 1.69 times higher for course takers. As expected, there was a statistically significant relation between first-term academic standing and graduation rates for all students ($\chi^2 = 15.39$, $df = 1$, $p < .0001$, $\phi' = .15$), such that the odds of graduating were 1.93 times greater for students in good academic standing their first term. Students with higher ACT scores also graduated at a slightly higher rate ($\chi^2 = 11.71$, $df = 1$, $p = .001$, $\phi' = .13$). However, graduation rate was not related to class rank ($\chi^2 = 2.46$, $df = 1$, $p = .117$, $\phi' = .06$). There was a statistically significant interaction between GROUP and academic standing ($\chi^2 = 7.14$, $df = 1$, $p = .008$, $\phi' = .10$). Table 6 and Figure 4 provide a summary of these results. Table 6 provides a summary of the differences in graduation rates between the groups by academic standing. Figure 4 shows clearly the Group × Academic Standing interaction and the graduation rate for the entire population for comparison. Compared with non–course takers, course takers had relatively stable graduation

TABLE 6
Numbers and Percentages of Students Graduating by Group and Academic Standing at the End of the First Term

	Graduating (n)			Graduating (%)	
Academic standing	*Yes*	*No*	*Total academic standing*	*Relative to group*	*Relative to academic standing*
Course takers					
Academic difficulty	14	17	31	4.0	45.2
Good standing	171	149	320	48.7	53.4
Total	185	166	351		52.7
Non–Course takers					
Academic difficulty	4	36	40	1.1	10.0
Good standing	151	160	311	43.0	48.6
Total	155	196	351		44.2

rates across first-term academic standing. Non–course takers in academic difficulty had considerably lower graduation rates with only four of the 40 students in this group graduating. Course takers in academic difficulty had a graduation rate 35.2% higher than did non–course takers in academic difficulty. A test of proportions revealed that the difference in graduation rates between course takers and non–course takers in academic difficulty was statistically significant, with 97.5%

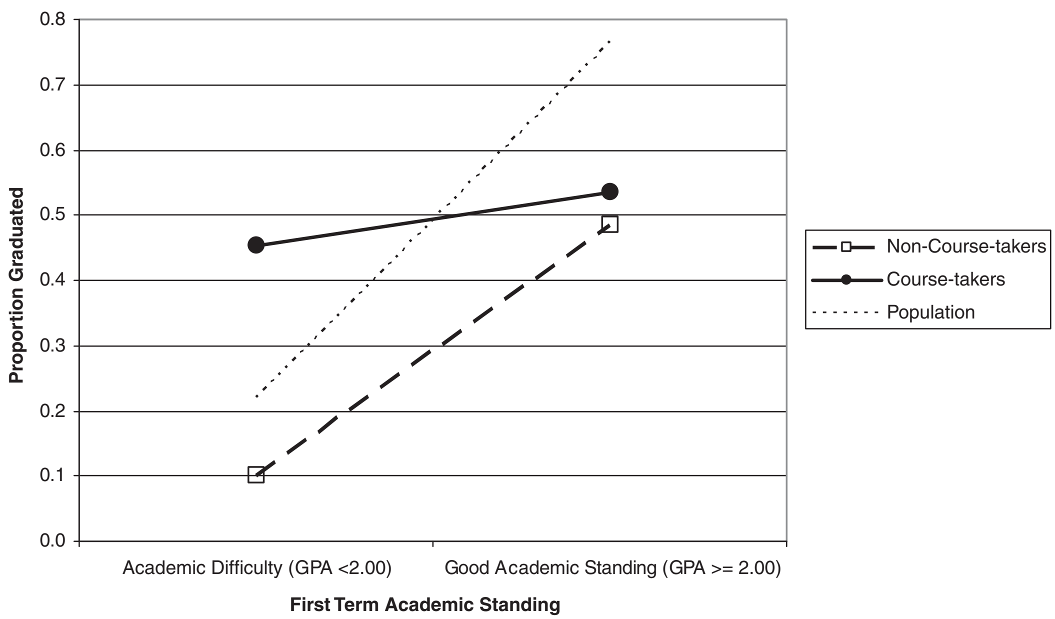

FIGURE 4 Proportion graduated as a function of first-term academic standing.

CIs around the difference equal to [0.14, −0.60]. However, the difference in graduation rate between these groups in good academic standing was not statistically significant. In particular, whereas course takers had a graduation rate 4.8% higher than did non–course takers, the 97.5% CI was [−0.04, 0.14].

DISCUSSION

Our article opened with the discussion of how large the dropout problem is in numerous settings, and thus poses a challenge for what can be done to ameliorate it. The results of the study suggest that part of the solution lies in the teaching of learning strategies. This study has shown that first-term, low-ability students enrolled in the learning strategies course (a) maintained a higher mean TGPA throughout their first year and into their second year of study, (b) were more likely to be retained during this period, and (c) had higher graduation rates relative to students not enrolled in this program but of comparable ability and demographic makeup.

These results suggest that enrollment in this program helps students achieve a higher level of academic performance and persistence than would have occurred otherwise. That is, first-term students taking this course tended to fall in the bottom two quartiles of academic ability as measured by high school class rank and standardized test scores. Students with this level of academic ability tend to perform poorly and have higher attrition rates than do higher ability students. However, the findings of this study suggest that students taking the learning strategies course benefited from the self-regulatory strategies taught. With respect to this last point, it is notable that the course takers in academic difficulty during their first term had higher graduation rates than comparable non–course takers. While there may be other attributions for why these students benefited, for example, the connection to the community that the students received, it would appear that the strategies learned helped protect students from poorer academic performance and attrition over the course of their first year, into the second, and even increased the likelihood of graduation.

The reasons why our course worked, that is, the factors that might have affected the power of this intervention, were the course content and instructional design. The content of the course was supported by the theoretical model of four strategies and eight substrategies that were used throughout the 10 modules of the course. The strategies were based on the McClelland model (McClelland, 1979), and elaboration of the substrategies was based on the Tuckman model (Tuckman et al., 2008). The strategies and substrategies served as tools for understanding and applying the course content.

An instructional role was also supported by the design of the course, namely the use of computer-based performance activities that enabled students to engage in active learning-by-doing, which facilitated the learning process and helped students overcome the challenges of technology use. The instructional design also provided students with a clear structure of their expectations and a timetable for achieving these expectations. It is likely that the positive net result of the combination of content and design contributed to the students' gains in academic performance.

The results of this research hold particular importance for other universities seeking to improve the academic performance of first-year students and to increase their likelihood of retention and graduation. However, one of the additional implications of the findings of this study may be that the teaching of learning strategies, as taught in this study, can help students other than those enrolled in universities succeed academically. Examples of this would be teaching learning strategies to high school students or students pursuing GEDs. This would enable younger students and nontraditional students to be successful in pursuing degrees in a timely manner and facilitate their academic advancement. Our learning strategies course has been used successfully in a number of high schools that resulted in increases in GPA relative to matched controls (Tuckman, 2007), thus contributing to the generalizability, or external validity of our research. According to Fraenkel and Wallen (2006), "the extent to which the results of a study can be generalized determines the *external validity* of the study" (p. 104). We recommend, therefore, that the learning strategies approach be applied to as many levels of education as possible.

LIMITATIONS

As is true in any study of this type, there were a number of limitations. First, because of the nature of how students registered for the course, it was not possible to randomly assign students to the two groups. In particular, students self-selected into the course and, while an attempt was made to match the comparison group as closely as possible to students who took the course, uncontrolled motivational differences may still be present. Although random assignment would have been optimal, it was not an ethically viable option because it could have prevented some students from taking a course explicitly offered to help them academically. Nevertheless, future research needs to control for this self-selection problem. One way to do this is to assess the motivational characteristics of an entire cohort during the first term of enrollment. Motivational characteristics can then be assessed and used, in addition to the variables of the present study, as matching variables and/or covariates. We are currently underway in collecting these data.

A second limitation is the small number of cohorts we had available to us combined with the relatively small number of first-term students who take this course. Given the limited number of students, it would have been preferable to collapse across cohort. Furthermore, it is generally agreed that seven third-level clusters (cohorts in this case) is small. However, the changes in selectivity of the admissions process implied a lack of independence among students within cohorts, particularly with respect to ability measures such as ACT and high school class rank. Students within a cohort were likely to be similar with respect to academic ability more so than students between cohorts. Including cohort as a third-level variable specifically takes into account this lack of independence as well as allowing for an estimation of the variability in the mean level and rate of change of term GPA because of differences in the cohorts. Nevertheless, further research should be conducted whereby additional cohorts are studied.

It is also possible that the higher overall achievement of course takers might be the result of their attempting fewer courses per term. However, this turns out not to be the case in this study. Course takers did not differ significantly from non–course takers in either the number of courses or number of hours per term. The average number of courses per term was 3.64 and 3.55, and the number of hours per term was 14.55 and 14.15, for course takers and non–course takers, respectively. A repeated-measures multivariate analysis of variance revealed no significant differences on these measures as a function of group, $F(2, 339) = 0.35$, $p = .698$, $\eta_p^2 = 0.002$. There was also no Group × Cohort interaction, $F(12, 678) = 1.32$, $p = .201$, $\eta_p^2 = 0.02$. These results suggest that it would have been unlikely that differences between the groups were, to any significant extent, the result of differences in the number of courses or hours taken per term.

AUTHOR NOTES

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