



Cross-Validation of Persistence Models for Incoming Freshmen

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Abstract

This study was intended to serve as an example of cross-validating results from student persistence prediction models that employed commonly available pre-college student characteristics. The study investigated whether the accuracy of predicting student persistence would vary because of the use of present-year vs. previous-year parameters on present-year data, and whether the same set of predictors would change in terms of predictive efficiency between years. Institutions with selective, liberal, and open admissions policies had consistent persistence prediction odds ratios across time regardless of the data on which model parameters were generated. As expected, all institutions demonstrated lower accuracy rates at higher persistence criteria, and accuracy rates differed between different sets of model parameters. The ACT Composite scores emerged as consistently stable, significant predictors of persistence. The paper concludes with a discussion of procedural issues to consider when using logistic regression to predict persistence.

Introduction

Many issues weigh upon the minds of administrators at higher education institutions. One of the more prominent among these issues is student persistence. According to Brawer (1996), approximately 50 percent of the freshmen enrolled in colleges and universities do not finish their degrees. However, many college counselors and administrators see persistence as a fundamental indicator of student success in postsecondary education (Kern, Fagley, & Miller, 1998). With such a large percentage of students failing to persist to graduation, it comes as no surprise to see an increase in efforts to identify factors related to student persistence.

While some institutions have lower persistence rates than others, facilitating student persistence is valuable for both institutions and students. For instance, Tinto (1993) noted that reduction in financial resources from external funding agencies (e.g., endowments, state government, etc.) is made more problematic by loss of income because of student non-persistence. For students who leave campus before graduation, resources used for recruitment, orientation, and support services are rarely recovered. Tinto also indicated that in extreme cases, declining enrollments and high non-persistence rates could lead to the collapse of an institution.

From a student's perspective, facilitation of persistence is also important. Were a student to terminate his/her postsecondary education before obtaining a degree, the student is more likely to experience a loss of future income, as well as experience higher levels of frustration and lower self-esteem (Tinto, 1993). Furthermore, students who persist to graduation often have easier access to prestigious positions in society and experience more societal rewards (Tinto).

No doubt, institutions and students will generally benefit from student persistence to graduation. However, if an institution is to play an active role in influencing students to remain enrolled, the institution needs to identify students who will benefit from interventions known to have a positive impact on persistence (Levitz & Noel, 1985). Furthermore, many interventions need to be in place from the time students arrive on campus (Sadler, Cohen, & Kockesen, 1997). This need translates into a common purpose for persistence studies: to develop an early warning system designed to identify students at-risk for non-persistence (Lenning, 1982).

With a goal of early intervention in mind, identification/prediction of incoming freshmen at-risk for non-persistence is necessarily based on pre-college data. Because institutions cannot know whether students *actually will* persist or not before coming to campus, the only recourse for predicting persistence is to use a model with pre-college data from previous year(s). Doing so assumes that the predictive model, generated on a different group of students, is applicable to the current cohort. With the changing characteristics of today's college student populations (e.g., age, financial assistance, race/ethnicity), such an assumption may not be tenable. If the assumption is false, an institution's predictions will be inaccurate, and resources earmarked for programs intended to improve persistence will not be spent on students who really need them. Therefore, the purpose of this paper was to conduct a cross-validation study that investigated the stability of persistence prediction models between two consecutive incoming postsecondary student cohorts.

Literature Review

It is tempting for researchers to look for common indicators of student persistence that apply across a range of institutions. However, the range of campus environments and sub-environments that exist make such research prone to overlooking important predictors *within* specific institutions. Though this study used the same model at all institutions, analyses were conducted *within* four individual institutions. The following review of literature will briefly discuss factors commonly associated with student persistence found at many institutions, predictors identified by researchers within specific institutions, and an approach using this information to identify students at-risk for non-persistence.

Predictors of Persistence Across Institutions

A number of factors have emerged as predictors of year-to-year persistence across multiple institutions. For instance, Horn and Carroll (1998) found that students who left college before their second year and never returned tended to be older, have children, and worked full-time relative to students who returned. Other common factors shown to be related to student persistence include tuition and debt load (Cofer & Somers, 1998), behavioral intentions, general attitudes toward higher education, social and academic integration, and student/institutional fit (Cabrera, Castaneda, Nora, & Hengster, 1992; Tinto, 1997; Tinto, 1993).

College GPA has also consistently shown to have a strong relationship with persistence (Braunstein, McGrath, & Pescatrice, 2000; Gillespie & Noble, 1992; Johnson & Molnar, 1996; Kern, et al., 1998; Tinto, 1993). Though a powerful predictor of student persistence, college GPAs are unavailable for incoming freshmen. Thus, researchers often must take advantage of the relationship between

college GPA, high school GPA, and standardized test scores by using pre-college academic variables instead of college GPA to predict persistence (ACT, 1997).

Within-Institution Predictors of Persistence

Many studies of persistence focus on results from *within* individual institutions. For instance, certain student personality types, self-efficacy, empathy, and physical fitness, as well as dissatisfaction "over the mismatch between their expectations and their experiences at the institution" (Zhang & RiCharde, 1998; p. 6) were significantly related to freshman student persistence. Kern et al. (1998) found that ACT scores, information processing, selecting main ideas, self-testing, and the composite of motivation, time management, and concentration had indirect effects on non-persistence through college GPA. This last set of findings was considered most important for two reasons. First, many of these skills and attitudes can be taught. Second, the influence of these variables on GPA can be investigated, followed by the influence of GPA on persistence (Kern et al., 1998).

Johnson and Molnar (1996) found that the odds of persistence for Black students were 50 percent greater than for other groups, after controlling for other academic and social variables. Other findings indicated that pre-enrollment variables (i.e., high school GPA, ACT Mathematics scores, etc.) and post-enrollment variables (i.e., satisfaction with major, expected vs. actual grades, etc.) could be used to identify student and institutional characteristics related to college student persistence (Gillespie & Noble, 1992).

Practical Application of Persistence Research

The studies cited above provided lists of variables potentially important to consider when studying persistence. However, the great diversity of environments and sub-environments within postsecondary institutions renders within-institution persistence analyses nearly a necessity.

An example of a within-institution study was Nichols, Orehovec, and Ingold (1998), who discussed using some of the variables above with logistic regression to identify incoming freshmen who were at-risk for non-persistence. Nichols, et al. found that by using estimated conditional probabilities of success based upon models developed on their 1993 cohort, they could predict with reasonable accuracy the students who were non-persistence prone in their 1995 cohort. Students who did not meet the probabilistic criterion were considered at-risk, and were subsequently provided with additional services or resources (e.g., academic advising or counseling) designed to improve the probability of persisting.

A similar approach was demonstrated in Sadler, et al. (1997), who applied logistic regression to identify students at-risk for not persisting into their second year of college using five different criterion levels of estimated conditional

probabilities of persisting. Staff would identify and contact at-risk students, and subsequent services would ideally meet whatever student needs that may exist on a one-to-one basis. The intent of the plan was to improve persistence through interaction with these at-risk students at multiple points in time (e.g., prior to the start of the fall semester, after the third week of classes, at the end of the first semester).

Though statistical identification of at-risk students exemplified in Nichols, et al. (1998) and Sadler et al. (1997) holds promise, there are some potential limitations associated with using statistical identification alone. These limitations include (but may not be restricted to) the following:

1. Highly unequal percentages of persisters and non-persisters will impact logistic regression parameter estimation. Therefore, results may be substantially affected by an institution's overall persistence rate.
2. Logistic regression results can be very complicated, but both studies address this problem by making the results user-friendly in terms of probabilities. However, in-house staff may not have the statistical savvy required to obtain and fully explain the results to colleagues.
3. Predictive models obtained from students in one year are often assumed to validly predict persistence for subsequent cohorts of incoming freshmen to a similar degree of accuracy.

A solution to the first limitation would be to augment statistical logistic regression results with other types of information (e.g., focus groups, contact with residence hall assistants (RAs), etc.) when the ratio of persisters to non-persisters is relatively high, and the second limitation can be overcome by staff development or hiring practices. The final potential limitation does not have an easy solution. Should predictors (and their associated model) from one year do a poor job of predicting persistence of a subsequent cohort, identification of incoming freshmen at-risk for leaving campus would be based upon faulty information. The third limitation was the focus of this study.

Methodology

Participants

Student data came from institutions selected on the basis of admissions selectivity, because research has shown that the persistence rates tend to vary as a function of institutional selectivity (Tinto, 1993). This difference in persistence rates could affect the functioning of the logistic modeling; hence stratification on selectivity was intended to control for this effect. The schools used for this study were randomly selected, within selectivity classification,

from a group of 24 that participated in the ACT Retention Service for both the 1999-2000 and 2000-2001 academic years, and had more than 500 student records each year. Institutions with fewer than 500 student records were omitted from the selection pool, because small sample sizes in non-persistence groups could result in independent variables nearly completely predicting persistence. This situation could also arise when there are large imbalances between the percentage of students persisting and not persisting. Such "quasi-complete separation of data points" would inhibit maximum likelihood estimation of parameters and logistic model fit could not be achieved.

This study used data from consecutive years because of data availability. However, studies such as this conducted as part of an ongoing persistence research program will often skip a year in the data. This is because data would be gathered from applicants prior to enrollment in the fall of year one, and persistence status would not be known until the fall of year two (using the same definition of persistence as is used in this study). Those results would then be used for students in the fall of year three. A shorter period of time between groups of enrollees, such as was used in this study, may increase the degree of observed predictive stability, thereby biasing the present results toward conclusions of model stability.

All institutions in the study were four-year institutions. Though study of persistence at two-year institutions is needed, such schools experience more complexity in defining persistence than four-year institutions because of relatively high transfer rates, percentages of part-time students, percentages of students seeking professional/personal enrichment (rather than a degree), etc. Subsequent research based upon the present study may look at two-year institutions.

Because the four-year institutions in the sample pool varied in terms of size, type of governance, selectivity, and other factors, it was decided that randomly sampling one school from each of five selectivity classifications would control the impact of selectivity, and give other relevant institutional characteristics an equal chance of being represented in the results. For the purposes of this study, institutions were initially classified into five selectivity groups based upon the criteria in Table 1, but the final classification was based upon institutional self-report.

Table 1
Selectivity Definitions

Typical Pre-College Academic Characteristics of Student Body		
Self-Reported Admissions Selectivity	Interquartile Range of Avg. ACT Comp. Scores	High School Class Rank
Highly Selective	27-31	Majority of students in top 10% of h. s. graduating class
Selective	22-27	Majority in top 25%
Traditional	20-23	Majority in top 50%
Liberal	18-21	Some students from lower 50%
Open	17-20	All high school graduates accepted, to capacity

Institutional self-report resulted in mean ACT scores at the colleges in this study not necessarily falling within the typical ranges in Table 1 (compare to Table 2). No highly selective institutions with more than 500 records had persistence data for both the 1999-2000 and 2000-2001 school years, so data from only four schools, one from each of the remaining selectivity classes, were used.

Table 2 presents the number of student records available and percent of students returning for a second year for each institution per school year.

Table 2
Institution Characteristics by Admissions Policy

Self-Reported Admissions Selectivity	Number of Complete Student Records Available					
	1999-2000 Data			2000-2001 Data		
	N	Pct. Return	Mean ACT Composite	N	Pct. Return	Mean ACT Composite
Selective	3,509	85	24.3	3,426	87	24.5
Traditional	817	78	23.2	908	79	23.3
Liberal	1,049	81	22.7	1,433	80	22.8
Open	1,038	68	20.2	1,091	73	20.1

Within selectivity groups, only one institution was randomly selected. This was done for two reasons. First, for consistency with other persistence research, this study was looking at persistence *within* institutions. This required repetition of all analyses as many times as there were institutions. Second, because the sample pool lacked representativeness of any readily defined population of institutions, generalizability was curtailed. As such, the additional computational complexity of including individual analyses of more institutions would add little in terms of interpretation and use of results.

Definition of Dependent Variable: Persistence

A student described as a “persister” was one who initially came to campus in the fall was continuously enrolled up to and including the following fall. All others who took a “break” or permanently left before enrolling for the following fall were defined for this paper to be non-persisters. This contrasts with other common definitions, such as when a persister enrolls in consecutive fall terms—even if he/she does not enroll in the interim spring term.

The decision to use a definition of persistence relative to the second year was made for three reasons. First, undergraduates who complete their first year of education and subsequently reenroll in their second year have a higher likelihood than not of obtaining their degree (Horn & Carroll, 1998). Second, nearly a third of all students leave postsecondary education before reaching their second year. This is a higher proportion than all other years combined (Horn & Carroll). Third, the first to second year attrition rate is generally the most significant determinant of ultimate graduation rate for an institution (Levitz, Noel, & Richter, 1999).

Independent Variable Definitions and Selection

This study advocated identifying and using institution-specific predictors for within-institution persistence research. However, six predictors commonly found within-institution studies were chosen for use within each school. The primary reason for this was that the study’s purpose was to look at the applicability of a single prediction equation and its constituent variables based on a common model for two separate years of students, rather than identifying an optimal model. The technique, in turn, could be replicated by practitioners using variables appropriate for their own student populations. Though the common model may not be optimal for a single institution, the predictors were selected on the basis of findings in other articles and substantive concerns. The intent of their use was for the present results to have some applicability to different institutions, while recognizing that better predictors may be available for local campuses. In practice, institutions looking to replicate the present study with their own students may wish to look beyond the more global set of predictors and employ relevant institution-specific variables.

The six predictor variables included in this study were selected because they have been used in other research or were of interest to broaden the demographic coverage of the model. Furthermore, all were pre-college variables. The first predictor was in-state/out-of-state, reflecting students’ state residency statuses. The second variable was commitment to one’s major, measured using a three-point Likert rating of how sure students were of an intended major that they listed when applying to take the ACT Assessment. Third, this study looked at the choice of colleges students were attending. Students who were attending their first or second choice institution were grouped, and students attending their 3rd-6th choice were also grouped, thereby creating a dichotomous institution choice variable.

A fourth predictor was gender. The fifth predictor was race/ethnicity. Because of model convergence problems with more specific classifications, race/ethnicity was dichotomized into Caucasian/Minority for this study.

Though high school GPA is often found to be an efficient pre-college predictor of persistence, the sixth predictor selected was ACT Composite instead. This decision was made because ACT Composite score and high school GPA are both often found to be efficient predictors of persistence in-and-of themselves, but collinearity between the two could give rise to results that mask the efficiency of either predictor. Because the researcher was more concerned with the stability of ACT Composite than high school GPA as a predictor and did not want the issue of collinearity to be a factor, ACT Composite score was the only pre-college cognitive variable used.

In practice, the selection of variables depends greatly

on the purpose of one's persistence study. In the present study, variables were selected only as indicators of risk for non-persistence with no accompanying interventions for at-risk students. Under these conditions, one of the most important factors in selecting variables is whether the predictive efficiency of the overall model is maximized. Should there be interventions, however, we need to attend not only to getting an efficient model, but also to having variables that can be manipulated through planned intervention. Because only two of the present variables can be manipulated (e.g., remedial courses can improve academic proficiency, and career/major counseling programs can improve student/major fit), this model would be of limited use in helping an institution to appropriately implement persistence-enhancing interventions.

Scope of Investigation

This study will focus on predicting persistence using pre-college data for incoming freshmen. This pre-college focus is based on the notion that students at-risk for non-persistence may require intervention within the first few weeks of the freshman year (Zhang & RiCharde, 1998). At-risk students often require immediate attention, such as special recruitment, admissions, orientation practices (e.g., placing special emphasis on clearly communicating what the institution expects from the students, and what students can expect from the institution; see Brawer, 1996; Kim & Sedlacek, 1996; Kuh, 1991; Tinto, 1993), community-building activities (Tinto), mentoring programs (Brawer), advising programs (Wang & Grimes, 2000), and the like. These activities/programs require resource expenditure in order to be successful. As such, institutions want to be confident that their resources are being spent on correctly identified students.

Analysis

In order to satisfy the purpose of this study, there were two foci of analysis. The first focus was on the general stability of each variable's predictive efficiency. Logistic regression was performed on 1999-2000 data, and again on 2000-2001 data for each of the institutions using the set of predictors identified earlier. Stability of each variable's predictive efficiency was assessed through the use of a chi-square test for the significance of the difference between non-standardized regression coefficient magnitudes across years. Because non-standardized logistic regression coefficients are asymptotically normal when necessary assumptions are met, dividing the difference between paired coefficients in each model by a pooled standard error and then squaring the result gives a statistic that is distributed as a chi-square with one degree of freedom. Statistically significant values for this statistic (i.e., $p \leq .05$) for a given variable might be considered evidence arguing against use of the variable, as it would suggest that the variable functions differentially depending on the cohort. However,

this is not the case if discrepancies are statistically significant, yet the variable predicts persistence at a statistically significant level of efficiency in both years (see discussion of ACT Composite in Results section). One should note that the statistic described above is *not* the Wald Test, as the Wald is not intended to test the difference between two parameters in equations derived from separate samples.

A second focus of the analyses dealt with determining whether the use of the previous year's equation would effectively predict persistence in a new sample (Kleinbaum, Kupper, & Muller, 1988). A cross-validation procedure was run analogous to that described by Pedhazur (1982) for ordinary least-squares regression. The 1999-2000 data served as the calibration sample and the 2000-2001 data as the validation sample. After obtaining separate logistic equations for the 1999-2000 and 2000-2001 data using the same set of predictors, the resulting equations were both applied to 2000-2001 data in order to generate two separate sets of predicted persistence statuses (e.g., predicted persisters and predicted non-persisters).

Within each institution, separate 2x2 contingency tables were created by crossing predicted and actual persistence status based on results of applying the calibration (i.e., 1999-2000) and validation (i.e., 2000-2001) sample equations to the validation data (see Table 3).

This process was replicated for each "predicted persister" criterion described later. These tables were

Table 3
Example 2x2 Persistence Status Table

		Predicted Persistence Status	
		Persisters	Non-Persisters
Actual Persistence Status	Persisters	N Correctly Predicted Persisters	N Incorrectly Predicted Persisters
	Non-Persisters	N Incorrectly Predicted Non-Persisters	N Correctly Predicted Non-Persisters

compared according to accuracy of predicting persisters and non-persisters separately, as well as through accuracy rates (i.e., overall percentage of correct predictions). This author has been unable to find a set of criteria to use when classifying differences in accuracy rates as being small, medium, large, etc. As a result, this question has to be considered from a more pragmatic, institution-specific perspective.

To facilitate understanding of accuracy rates from a pragmatic perspective, suppose there are two fictitious institutions, A and B. Institution A has admitted 100 students, whereas Institution B has admitted 10,000

students. Furthermore, suppose that each institution attempts to identify students at-risk for non-persistence, and has data available to perform a cross-validation study such as exemplified by the present study. Assume that in both cross-validation studies, an increase of only one percent in accuracy rate is observed when using present- vs. prior-year parameters.

At Institution A, the one percent accuracy rate increase means that only one additional student would be incorrectly classified if the institution continued to use the prior year's parameters for prediction. At Institution B, however, that same one percent would result in 100 students being incorrectly classified when using the prior year's parameters—many students would receive services that were unnecessary, and/or many would not receive necessary services. As institutional leaders, one of the tough decisions to make is whether the *number* of students affected by differences in accuracy rates is large enough *at a specific institution* to revisit how one uses a statistical model for identifying at-risk students.

Finally, the two 2x2 tables within each institution and criterion classification were combined to form 2x2x2 tables, representing the following three crossed dimensions: (prediction equation year—'99-'00, '00-'01) x (predicted persistence—predicted left, predicted stayed) x (actual persistence—actually left, actually stayed) (see Table 4).

Table 4
Example 2x2x2 Persistence Status Table

		Predicted Persistence Status				
		Parameter Year '99-'00		X	Parameter Year '00-'01	
		Persisters	Non-Persisters		Persisters	Non-Persisters
Actual Persistence Status	Persisters	N Correctly Predicted Persisters	N Incorrectly Predicted Persisters	N Correctly Predicted Persisters	N Incorrectly Predicted Persisters	
	Non-Persisters	N Incorrectly Predicted Non-Persisters	N Correctly Predicted Non-Persisters	N Incorrectly Predicted Non-Persisters	N Correctly Predicted Non-Persisters	

A Breslow-Day test for homogeneity of odds ratios (Breslow & Day, 1980) was conducted on each 2x2x2 table to determine whether odds ratios for 2x2 tables from each pair of parameter years differed. The Breslow-Day test is a standard result generated by some statistical programs. However, some programs may not generate this statistic. In such situations, a viable alternative would be to use other chi-square tests that permit analysis of a 2x2x2 table. Discrepancies in prediction accuracy and/or rejected null hypotheses under the Breslow-Day test would support the argument that the two equations do not permit similar prediction accuracy levels, thereby calling into question the practice of using results from previous year's students to make probabilistic predictions about students coming to campus for the present year.

To establish predicted persistence status, estimated

probabilities of persistence generated for the second analysis focus were put through three recoding procedures, as described in Sadler et al. (1997). For the first criterion, if a student's estimated probability equaled or exceeded 0.50, he/she was classified as a predicted persister. Otherwise, he or she was predicted not to persist. Second, students were also classified relative to an estimated probability of persistence of 0.70. Finally, a similar classification process was carried out relative to a probability criterion of $\hat{p}=0.85$. Multiple definitions of what constituted a predicted persister were necessary because the accuracy of prediction results and relationships between predicted and actual persistence were hypothesized to vary as a function of the persistence criterion.

Results

Stability of Predictor Efficiency

Absolute predictor efficiency. In determining accuracy of predicting persistence using the previous year's model, the first focus in the analysis looked at how efficient each variable was in predicting retention from one year to the next. Table 5 shows that ACT Composite score stood out from the rest as a consistently significant predictor, where its odds ratios significantly differed from 1.0 for both years at all institutions. Other examples of efficient predictors were In-state/Out-of-state, Sureness of Major, and Gender.

Changes in predictor efficiency. As seen in Table 5, nearly all differences between model parameters were statistically *insignificant* at $p = .05$ from one year to the next, regardless of predictor and institution. The only exception was ACT Composite at the open institution, where the p-value was 0.027. Though the difference was statistically significant, ACT Composite score was still an efficient predictor for both years. Even with a significant difference in efficiency, the fact that it was a statistically significant predictor in both years allowed Composite scores to maintain their viability for use in a model.

As seen in Table 5, the direction of relationships between predictors and persistence sometimes varied between years (e.g., odds ratios changed from being less than one to greater than one, or vice versa). For instance, Caucasian/Minority group membership was positively associated with persistence in 1999-2000, but negatively in 2000-2001 at the traditional institution. On the other hand, ACT Composite score was consistently positively associated with persistence, where higher scores were associated with a greater probability of persisting.

Predictive Accuracy: Cross-Validation

Critical to the investigation of persistence prediction accuracy is the second analysis focus: stability of prediction accuracy. This stability will be described from two different vantage points: comparing among predicted persistence criteria, and comparing among calibration/validation parameters.

Table 5
Comparison of Logistic Regression Parameters

Variable	1999-2000 Data (Calibration Sample)			2000-2001 Data validation Sample)			Test for Diff. In Parm. Est.		
	Parm Est.	Pr. Chi-Sq.	Odds Ratio	Parm Est.	Pr. Chi-Sq.	Odds Ratio	Chi-sq.	Pr. Chi-Sq.	
N=3,509 Selective Institution N=3,426									
Intercept	-1.030	0.009	.	-1.277	0.001	.	.	.	
In/Out State	0.009	0.965	1.009	0.405	0.037	1.500	1.868	0.172	
College Choice	0.135	0.269	1.145	0.076	0.582	1.079	0.105	0.746	
Sure of Ed. Major	0.295	0.000	1.343	0.266	0.000	1.305	0.082	0.774	
Gender	-0.161	0.095	0.851	-0.245	0.018	0.783	0.348	0.555	
Cauc./Minority	-0.030	0.799	0.970	0.045	0.727	1.046	0.184	0.668	
ACT Composite	0.093	0.000	1.097	0.096	0.000	1.101	0.030	0.863	
N=817 Traditional Institution N=908									
Intercept	-2.169	0.000	.	-1.294	0.023	.	.	.	
In/Out State	0.435	0.019	1.545	0.601	0.001	1.824	0.423	0.516	
College Choice	0.263	0.257	1.300	0.308	0.215	1.360	0.018	0.894	
Sure of Ed. Major	0.093	0.438	1.098	0.407	0.001	1.502	3.469	0.063	
Gender	-0.258	0.141	0.773	-0.227	0.175	0.797	0.016	0.899	
Cauc./Minority	0.480	0.038	1.615	-0.137	0.575	0.872	3.362	0.067	
ACT Composite	0.110	0.000	1.116	0.063	0.003	1.065	2.354	0.125	
N=1,049 Liberal Institution N=1,433									
Intercept	-1.374	0.013	.	-0.764	0.094	.	.	.	
In/Out State	0.444	0.027	1.559	0.078	0.650	1.081	1.915	0.166	
College Choice	0.214	0.308	1.238	0.162	0.419	1.176	0.032	0.858	
Sure of Ed. Major	0.165	0.143	1.179	-0.015	0.870	0.985	1.525	0.217	
Gender	-0.166	0.304	0.847	-0.404	0.003	0.667	1.280	0.258	
Cauc./Minority	-0.164	0.418	0.849	0.037	0.823	1.037	0.593	0.441	
ACT Composite	0.098	0.000	1.103	0.096	0.000	1.101	0.005	0.946	
N=1,038 Open Institution N=1,091									
Intercept	-1.408	0.023	.	-0.932	0.098	.	.	.	
In/Out State	-0.269	0.552	0.764	0.235	0.534	1.265	0.733	0.392	
College Choice	0.050	0.771	1.051	0.462	0.008	1.587	2.833	0.092	
Sure of Ed. Major	0.118	0.210	1.125	0.181	0.059	1.199	0.227	0.634	
Gender	-0.032	0.814	0.968	-0.380	0.006	0.684	3.188	0.074	
Cauc./Minority	0.284	0.128	1.329	0.424	0.032	1.528	0.266	0.606	
ACT Composite	0.097	0.000	1.102	0.041	0.022	1.042	4.884	0.027	

Comparisons of prediction accuracy among persistence criteria. As expected, the use of logistic regression as a basis for modeling student persistence resulted in the highest accuracy rates being observed when using the $\hat{p}=0.50$ criterion, regardless of institution.

Results using the $\hat{p}=0.50$ criterion. When predicted persisters were classified according to whether their \hat{p} exceeded 0.50, large differences were not observed in prediction accuracy under the use of the two sets of parameters (see Table 6).

Results using the $\hat{p}=0.70$ criterion. Under the $\hat{p}=0.70$ criterion, accuracy rates for each parameter set differed little for the selective and liberal institutions, and only mildly for the traditional institution, with the largest difference being for the open institution. Yet, these results can be misleading, in that the traditional institution, rather than the open institution, had a statistically significant Breslow-Day statistic (see Table 6). This apparent contrast is resolved by considering that the Breslow-Day statistic in this table does not focus on accuracy rates, but on odds ratios between the 2x2 tables defined for predicted results from each set of parameters. As such, the greater variability in individual cell percentages for the traditional institution's tables accounted for the significant result.

Given the results above, had one simply reviewed accuracy rates, the significant difference in odds ratios would have been overlooked. Yet, using calibration parameters vs. validation parameters cut the accuracy of predicting non-persisters by about a third at the open institution. These results illustrate the point that institutions have to determine what is more important: accurately identifying non-persisters or persisters separately, or maximizing accuracy rates. Then, they have to balance their priority against how stable the predicted vs. observed persistence relationship is from one year to the next.

Results using the $\hat{p}=0.85$ criterion. For the selective institution, differences existed between percent correct predictions of persisters and non-persisters, depending on the parameters used. However, this difference in predictive accuracy did not result in a significant Breslow-Day test ($p=0.575$). Percentages for liberal and traditional schools were relatively stable, regardless of parameters used. Accuracy rates among different parameter combinations differed little for the liberal and traditional schools, though the open and selective institutions differed by 6.9% and 8.3% among parameter combinations. Furthermore, percentages of correctly predicted persisters and non-persisters were relatively stable. The Breslow-Day tests were statistically insignificant as well (see Table 6).

Results for the open institution warranted further consideration, as a counter-intuitive result emerged: the accuracy rate was higher using 1999-2000 parameters

than 2000-2001 parameters with the 2000-2001 data (28.3% and 21.4%, respectively). Why this result occurred is unclear, though it is likely related to the drop in number (as opposed to percent) of predicted persisters. Regardless, odds ratios between parameter years were very similar to each other, suggesting that taken as a whole, the predicted vs. actual persister relationship changed little between parameter years.

Discussion

Considerations for Using Statistical Techniques

This study was not intended to provide broad generalizations across many institutions, as persistence research is often best done *within* a single institution, and the variables selected for the present analyses were not necessarily optimal for the selected institutions. With this caveat in mind, the conclusions will be discussed below.

When considering all of the results above, several issues stand out. First, for some institutions, the use of the previous year's prediction equation on the present year's data will provide similar results to using the present year's equation. Yet, this is not always the case, as could be seen by the traditional institution under a $\hat{p}=0.70$ criterion. Also, the same predictors may have similar efficiencies from one year to the next at some institutions, but not at others.

For institutions that do not have extremely high or low persistence rates, the use of a criterion of $\hat{p}=0.50$ may be the most advisable for several reasons. First, when logistic models are used and all parameters converge, this criterion will provide the maximum accuracy rates. Second, this criterion is more easily understood by non-technical colleagues, as it simply represents whether students have a higher probability than not of returning. Though this criterion may have more falsely identified at-risk students than other criteria (an assertion founded on raw results on which Table 6 is based), more students will receive persistence-targeted programming, thereby reaching out to those students who might otherwise be overlooked.

The downside to using a criterion of $\hat{p}=0.50$ is that as many as half of the incoming freshmen are identified as being at-risk, a proportion representing many students. As such, relatively large amounts of financial and personnel resources are necessary to provide prescribed interventions. An unfortunate reality experienced by many institutions is that resources are limited. Thus, the selection of criterion to use when identifying students at-risk for non-persistence requires balancing priorities of serving as many students in as accurate a manner as possible, yet within a context of limited resources.

Another important issue to consider is selection of predictors. Ideally, pre-college predictors should be consistently efficient predictors of persistence and be readily available prior to arrival on campus. At the same time, when persistence programming will be provided for

Table 6
Accuracy of Predicted Persistence Using Calibration (99-00) and Validation (00-01)
Parameters on 00-01 Data

Admissions Policy	% Correct Pred. Using 99-00 Parns			% Correct Pred. Using 00-01 Parns.			Breslow-Day Results		
	Persisters	Non-Persisters	Accuracy Rate	Persisters	Non-Persisters	Accuracy Rate	N	Chi-Square	P-Value
P-hat=.50 Criterion									
Selective	100.0%	0.0%	86.7%	100.0%	0.2%	86.7%	3,426	Ñ-	Ñ-
Traditional	99.4%	2.6%	79.1%	99.9%	0.0%	78.9%	908	1.130	0.288
Liberal ¹	100.0%	0.0%	79.9%	100.0%	0.0%	79.9%	1,433	Ñ-	Ñ-
Open	98.1%	5.1%	72.8%	99.5%	1.4%	72.8%	1,091	0.001	0.976
P-hat=.70 Criterion									
Selective	99.1%	3.5%	86.4%	99.3%	1.8%	86.3%	3,426	0.889	0.346
Traditional	81.7%	28.8%	70.6%	88.3%	29.3%	75.9%	908	4.082	0.043
Liberal	94.5%	8.7%	77.3%	90.6%	18.1%	75.9%	1,433	0.714	0.398
Liberal	94.5%	8.7%	77.3%	90.6%	18.1%	75.9%	1,433	0.714	0.398
P-hat=.85 Criterion									
Selective	59.8%	57.2%	59.5%	70.6%	47.4%	67.5%	3,426	0.314	0.575
Traditional	30.5%	85.3%	42.1%	29.7%	83.8%	41.1%	908	0.274	0.601
Liberal	31.4%	80.2%	41.2%	30.5%	84.0%	41.2%	1,433	0.867	0.352

¹Denotes results that were identical, regardless of which year's parameters were used.

at-risk students, at least some of the predictors should be manipulable. In other words, the student characteristic(s) described by the predictor(s) should be manipulable.

An example of a suitable predictor was ACT Composite score. In this study, ACT Composite was a stable, efficient predictor of persistence at each school, and was available prior to the arrival of most students to campus. Furthermore, ACT Composite scores reflect student academic characteristics that can be manipulated through assignment to coursework at appropriate levels (e.g., remedial or standard courses).

Along with the practical issues above, there are important statistical considerations that require attention as well. When selecting variables for inclusion into logistic predictive models, it is important to consider how highly potential variables correlate with one another within the sample. Collinearity can result in inflated variance estimates for model parameter estimates, wrong signs and magnitudes of these parameters, and other troublesome outcomes.

While there is really no set standard for how high the intercorrelation needs to be before one worries about the impact of collinearity, it is well advised to perform collinearity diagnostics in any logistic regression analysis and deal with collinear variables that emerge based on rules appropriate for each diagnostic procedure. As discussed earlier, ACT Composite score and high school GPA have a non-trivial correlation with one another, and

both serve as efficient pre-college predictors of persistence. This correlation, or collinearity, would limit the stability of regression weights if both were included. This situation can result in misleading outcomes when trying to decide whether to use one variable or the other. If one's interest is in overall model efficiency instead of the functioning of specific variables, the inclusion of collinear variables is not a problem. One approach to this inclusion would be to create a single predictor that represents a combination of the two variables. In this way, the predictive efficiency of both variables is included in the model. One drawback is that information is lost regarding the efficiency of both variables individually. Should one wish to use *only one* of the predictors, a simple solution is to run the full model first with one of the collinear variables, and then re-run the full model with the second collinear variable—but not both. Then, simply include the predictor that had the most impact on the efficiency of the full model.

Considerations for Interpreting Statistical Results

Though it may be tempting to simply look at the probability of persistence as an identifier of students at-risk for non-persistence, this practice has limitations associated with it. For instance, there is the possibility of erroneously assuming similar predicted/actual relationships from one parameter year to another when using a model to determine appropriate interventions.

A second issue is that moderate-to-substantial differences in average \hat{p} values between parameter years can impact the accuracy of identifying at-risk students. Based on a result in Hosmer and Lemeshow (1989), an institution's average \hat{p} value for a given year is equal to the proportion of students persisting in the same year. As such, historical patterns can be investigated for persistence rate stability by simply reviewing past trends in persistence rates. If stability is not observed in past years, then other approaches (e.g., non-statistical reviews of student records) should be employed. Simply starting the process in a given year and using the probability approach without first determining the stability of persistence rates may give rise to inaccurate or misleading results.

This study also demonstrated a further consideration: simply looking at selected percentages of correct classifications in absence of the "big picture" could be misleading. This conclusion stemmed from varied percentages in correctly predicted persisters, non-persisters, and accuracy rates as shown in Table 6, yet few significantly different odds ratios. From these results we can draw a conclusion that looking at only part of the picture can give different results than looking at the whole picture.

One reality often faced in postsecondary institutions is that simply identifying students as being at-risk is not helpful. With a limited amount of resources, only a portion of an at-risk student cohort may be able to receive services. Thus, researchers are often asked to select from the at-risk cohort a subgroup for whom persistence-related programs/resources would be most at-risk. One approach can be accomplished by first rank ordering the students from "most at risk" to "least at risk" on the basis of estimated conditional probabilities of persisting (p). Once ranked, researchers can then flag a specific percentage of students with the highest risk levels and assign them to programs. Note, this approach is oversimplified, as more information than just statistics may be needed for accurate assignments.

Considerations for Persistence Research Implementation: An Example

An example of using more than just a probability to identify at-risk students is a delayed compensatory at-risk model. Let us suppose that the probability modeling approach is used to identify at-risk students before they come to campus, and that all of the statistical concerns identified above have been dealt with as much as possible. Without any other information, the probability modeling approach may be all an institution can do for identifying incoming at-risk students.

An alternative to immediately assigning students to at-risk programs based on statistical analyses would be to also implement one-on-one contact with RAs, academic

advisors, faculty, and general outreach services, similar to the "three week checkup" for every new student as described in Nichols, et al. (1998). These contacts can be used to gather information about important predictors of persistence such as intent to leave the institution (Bean, 1982), attitudes about the social and academic environments (Bean, 1982), and fit between personal goals and actual experiences on campus.

As a conservative approach, any students identified as being at-risk by the personal contacts *or* by a given p criterion might be invited to partake in persistence-enhancing programming. On the other hand, students may be considered at-risk if both p *and* contacts recommend at-risk classification. Whether students are invited to initiate or continue participation in at-risk programming then becomes a decision based upon multiple sources of evidence, some of which may override the probability model in importance for decision-making.

Conclusion

In the end, promoting student persistence is not a simple task. The literature recommends that early intervention with students at-risk for non-persistence constitutes resources well spent (Sadler, et al., 1997; Tinto, 1993). Yet, some institutions have student bodies with characteristics that challenge attempts to identify at-risk students based on pre-college data. An institution may have stable predictive relationships from one year to the next or it may not, depending on selected predictors, classification criteria, base persistence rates, and admissions policies. If we are to use persistence prediction research to guide programming, we have to conduct proper preparatory analyses to ensure that our incoming student cohorts do not have a history of extreme nor rapidly changing persistence rates. Once this information is obtained, we need to regularly perform cross-validation analyses, or run the risk of assuming stable predictive relationships when such an assumption is not tenable.

As discussed above, using a probabilistic approach can have problems associated with it. Therefore, this approach would best be used in conjunction with other indicators of non-persistence risk, such as post-enrollment academic variables, personal contact, and the like. This information can be obtained through means as informal as local record keeping and RA visits, or as formal as using retention reporting services provided by institutions such as ACT.

Along with ongoing research, programs designed to promote persistence need to be in place at more points in time than just the initial contact with the campus (Sadler, et al., 1997). Failing to account for changes in the student body, both at admission and as students progress through school, increases the risk of using antiquated interventions on the wrong group of students. However, continued adjustment of programs based upon results

from research can result in substantial rewards for the institution, and ultimately, the students.

Recommendations for Future Research

Future research using the present methods may consider investigating the applicability of predictive models across types of institutions is important. The typology of institutions can be general or specific. For instance, institutions can be stratified based on selectivity, as done in this study. Or, they may be classified according to other characteristics, such as 2/4 year, public/private, etc. Regardless of how typologies are defined, information about and strategies for improving student persistence are in the best interests of institutions and students.

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