Work in Progress: Developing a Procedure for Identifying Indicators of ”Over-persistence”

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Introduction

This work-in-progress paper represents our initial approach to developing a procedure for identifying indicators of "overpersistence." This approach is one facet of a larger NSF CAREER project, "Empowering students to be adaptive decision-makers," to model student pathways using a ground-up curriculum-specific approach with the ultimate goal of helping students choose more strategic paths to graduation. We define "overpersisters" as those students who enter college with a specific major in mind and never sway from that choice, nor graduate in a timely manner. While persistence in and commitment to a major choice are generally viewed positively, some students become fixated on a major that may not be the best fit for them. These overpersisters often spend years in a degree program and eventually leave the institution with no degree, but potentially with a substantial amount of debt. Identifying academic events that cause these students to eventually withdraw from school is the first step towards creating better strategies through which they can persist and succeed in their undergraduate studies.

The concept of overpersistence is defined relative to a particular major, so a student who tries a different major before leaving the institution would not be considered an overpersister. We selected the discipline of Mechanical Engineering as a starting point because of its large enrollment and the first author's familiarity with the discipline. Our goal is to begin developing a procedure that will identify indicators of overpersistence and provide a foundation that will help to answer the larger research question: *In Mechanical Engineering, what academic events commonly lead to late dropout without changes in academic major?*

Known predictors of retention and dropout

A number of variables including institutional[1–3], financial[4–7], socioeconomic[8–11], as well as demographic and academic factors[12–16] have been investigated to determine their influence on college student retention. While all of these factors can play a role in a student's decision to either drop out or persist, both in college and in their respective majors, few of these factors are readily available to university advisors who are charged with assisting students in these decisions. Often advisors must use academic factors, such as GPA or course grades, to frame their recommendations to students. With this in mind, we look to the literature for potential indicators of student retention, or conversely of dropout, with an eye toward identifying risk factors for overpersistence.

Past research has identified three main academic factors; high school GPA, college GPA, and SAT or ACT test scores, as predictors of college student retention[5,7,12,14]. For example, Wohlgemuth et al.[5] determined that ACT scores were positively correlated with retention. Their analysis also indicated that high school rank was an indicator of student retention[5]. Similarly, a student's college GPA is another common predictor of retention. Specifically, in their study of those factors most salient to successful graduation, DesJardins, Ahlburg, and McCall[7] determined that those students with a higher college GPA were more likely to persist in their studies and graduate with their degree in a timely manner.

The majority of research on student retention has focused on student retention in college; however, some work has investigated the retention of engineering students within their declared major. Some of the same college retention factors (college GPA, performance in high school, and standardized test scores) have been shown to be indicators of retention in engineering. French[17] found high school rank, SAT math scores, college cumulative GPA, and motivation to be positively correlated with enrollment in engineering. Tyson[18] examined student grades in Physics and Calculus courses and found indications that low grades in these courses could predict a student leaving engineering. However, he also correlated earning an A in Calculus II with switching from engineering to computer science[18]. With these college and engineering retention and dropout factors in mind, we present an initial method for identifying potential risk factors for overpersistence.

Method

Sample. The sample for this initial study comes from a single land grant institution in the southeast over the period 1987-2004. Once a procedure is established, it will be applied to more recent data. We use six-year graduation deadline in the analysis, so our sample encompasses only those students who began school between the years 1987 to 1997. During this period, 891 students met the following study criteria:

- They were first-time-in-college students, not transfer students;
- They undertook a full-time course load in their first semester (12 credit hours);
- Their first degree-granting major was Mechanical Engineering (ME);
- Their last major was ME;
- They remained enrolled for more than one calendar year.

In short, the students in this sample **enrolled and remained in the Mechanical Engineering program** until either graduating or withdrawing from school, or at least until the end of this dataset (2004). The demographics of our sample were as follows: 11% were female, 89% were White, 6% were Black, and less than 3% were Asian. While we use data encompassing a six-year time limit of graduation for this study, we do recognize that many students take longer to graduate. Indeed, over half of the 204 students who did not graduate in six years did graduate within the bounds of the study period. This choice will be further examined when more recent data becomes available. We define overpersisters as first-time college students who enroll in a major, remain in school for at least one year, and then either leave the institution or are still enrolled in the same major after 6 years without graduating.

Procedure. For each construct, a single variable logistic regression is used to determine the variance in graduation explained by the construct. Including two closely related variables in the same model can cause confusing and even misleading results. Additionally, looking at each variable individually allows us to use the most data since records with missing data must be deleted listwise. In other words, a student cannot be included in the regression if they are missing any of the variables in that regression. The coefficient, β, can be used to calculate the log of the odds of an event (eq. 1). Positive values indicate that the presence of one unit increase of the variable increases the likelihood of the event. In this case, the event of interest is graduation.

$$\log(\text{odds of event}) = \beta_0 + \beta x \quad (1)$$

Initial Results and Discussion

In this sample, neither race/ethnicity nor gender, nor their combination, met the 0.05 significance level for entry into the model. While the lack of significance does not rule out the possibility of interaction with other variables, it does indicate that these demographic variables alone are not good predictors of six-year graduation in ME.

Because high school information has been shown to predict college success, we begin by examining high school GPA, high school rank, and high school rank divided by school size as related to a six-year graduation period for ME. As shown in Table 1, high school GPA explains the greatest variation.

Table 1. High School Variables

Model	Variables	df	N	Mean	SD	β	Max-Rescaled R^2
1a	High School GPA	1	878	2.78	.377	1.2537*	**0.0535**
1b	High School Rank	1	885	34.3	40.3	-0.0066*	0.0218
1c	High School Rank/High School Size	1	885	.136	.126	-1.8316*	0.0155

* p<0.05

SAT scores may also be used as either a total or as a component score with the SAT-Verbal indicative of the greatest variation as shown by the Max-Rescaled R^2 in Table 2 [19]. While it may seem counter-intuitive that SAT-Math does not explain a significant portion of the variation, recall that this is within a very specific group that has relatively high SAT-Math scores (with a median of 660 for our ME sample compared to 570 for the university during this period).

Table 2. SAT Scores

Model	Variables	df	N	Mean	SD	β	Max-Rescaled R^2
2a	SAT	1	891	1117	177	n.s.	-
2b	SAT-Math	1	891	598	153	n.s.	-
2c	SAT-Verbal	1	891	520	83	0.0024*	**0.0105**
2d	SAT-Math*SAT-Verbal	1	891	-	-	n.s.	-

* p<0.05

College GPA can be calculated either by term or cumulatively. In Table 3 we see that the first-semester term GPA is more explanatory than the term GPA for the second through fifth semesters. Note the increase in standard deviation after the second semester, possibly indicating the likelihood of some students continuing their coursework over the summer (third semester) while others choose to resume study in the fall. Also, note the loss of students beginning in the fourth semester. While the term GPA generally loses explanatory power with time, the cumulative GPA gains explanatory power, with substantial increases from semester 2 to 3 and 3 to 4. Although subsequent cumulative GPAs may be more elucidating, early indicators are of the most value for prevention. It is interesting to note that the first-semester term GPA is more powerful than the second semester cumulative GPA. By the eighth semester, the sample size is reduced to 871: with three students having graduated and 17 having left the institution.

Table 3. College GPA

Model	Variables	df	N	Mean	SD	*β*	Max-Rescaled R^2
	Term GPA						
3a	Semester 1	1	891	2.95	0.67	0.7529*	**0.0676**
3b	Semester 2	1	891	2.66	0.77	0.3669*	0.0215
3c	Semester 3	1	891	2.30	1.19	0.1782*	0.0124
3d	Semester 4	1	888	2.37	1.06	0.3310*	0.0347
3e	Semester 5	1	887	1.90	1.32	0.1221*	0.0070
	Cumulative GPA						
3f	Semester 2	1	891	2.79	0.65	0.6845*	0.0505
3g	Semester 3	1	891	2.72	0.61	0.8923*	0.0703
3h	Semester 4	1	888	2.68	0.58	1.0922*	0.0922
3i	Semester 5	1	887	2.62	0.55	1.1821*	0.0956
3j	Semester 6	1	885	2.60	0.54	1.2776*	0.1050
3k	Semester 7	1	878	2.58	0.53	1.3461*	0.1085
3l	Semester 8	1	871	2.57	0.53	1.3963*	**0.1169**

* $p<0.05$

Summary

Our results thus far indicate the feasibility of this initial approach in identifying key variables that are possible precursors of overpersistence. Our single variable approach is particularly applicable in the selection of highly correlated variables. In this sample, we found that: 1) the high school GPA served as a better predictor of overpersistence than high school rank variables; 2) SAT-Verbal was the only SAT variable with significant predictive power; and 3) cumulative GPA becomes more explanatory during each successive semester, but the first-semester term GPA is more powerful than the cumulative GPA after two semesters;. We also noted that only 17 of the 204 who did not graduate within six years left school after one year and before the eighth semester, meaning that most of the students who left without a degree had committed at least eight semesters of time and tuition to their chosen degree program.

Continuing Work

The continuing evolution of this project (both in scope and size) will next involve the use of more recent data to determine which findings hold true. Additionally, the pool of variables will be expanded to include specific course outcomes and other semester variables (e.g. number of hours attempted, number of hours completed). The goal of understanding these students is to be able to identify them early and help them make strategic decisions about defining and reaching their goals. The strategic pathways will be identified by studying students with similar indicators that adapted by choosing a different path of study. Phase II of the project begins in Fall 2017 with data collection on self-regulated decision making, major fit, and self-regulated learning in order to map real-world behaviors (major changes) to self-regulated decision-making theory[20].

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