Student Support Interventions and Predictive Analytics

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Abstract - The purpose of this inquiry was two-fold: the first was to identify a model to predict new students' first semester cumulative GPA and the second was to determine the fit of that model if the student experienced one or more student support intervention(s). Data from 12,507 new beginners from Fall 2012 and Fall 2013 were used to create a regression model for predicted cumulative GPA. This model included factors such as high school GPA, standardized test scores, low-income status, first-generation status, minority status, gender, and residency. Based on the predicted GPAs, potentially at-risk students were identified and some intervention services were targeted specifically to them. The latest data shows that students who experienced an intervention or had a combination of interventions had statistically significant higher GPAs and those who do not have any intervention. For deeper analysis, other factors such as registration in a high enrollment, high DFW courses and international status are also being examined.

Introduction

Within Indiana, there is a specific call to action to increase college completion. In 2012, the Indiana Commission for Higher Education (ICHE) adopted the *Reaching Higher, Achieving More* agenda which calls on state institutions to focus on three aspects: completion, productivity, and quality. For the completion goal, they call on all state institutions to achieve a four-year graduation rate of at least 50% by 2018 (Bepko and Moran-Townsend, 2012). Purdue University is not yet at that 50% mark as illustrated by Table 1 (Purdue University Data Digest, 2015).

Table 1: Purdue Retention and Graduation Rates

Cohort	1 Yr Ret	2 Yr Ret	4 Yr Grad	6 Yr Grad
2007	87%	77%	42%	71%
2008	87%	81%	46%	74%
2009	89%	83%	47%	n/a
2010	90%	84%	49%	n/a

Students cannot graduate if they are not initially retained, so efforts to increase first and second year retention have been emphasized at Purdue as well. This paper will highlight the effort to identify students at-risk of a low first semester cumulative GPA and using that to inform programmatic support systems.

Background

Researchers have a long history of investigating why students depart institutions of higher education. One of the most pervasive theories is Tinto's Interactionalist Model of Student Persistence (1975), which outlines the way in which student entry characteristics, goal commitment, institutional commitment, academic integration, and social integration interact with student persistence. In later revisions to Tinto's theory, it is proposed that a student's entry characteristics (including the ability to pay) affect their initial level of commitment to the institution and affect their perception of the institution's commitment to the welfare of the students as well as their potential to become integrated into the environment. (Braxton, Hirschy, and McClendon, 2004).

However, merely identifying these students is only part of the picture. It then becomes a question of what sort of supports, interventions, or services are targeted at these students to reduce their risk of low academic performance and/or departure. Although a student's entry characteristics can affect their initial institutional commitment, the college or university's actions can affect a student's *subsequent* institutional commitment and therefore reduce the risk of departure (Braxton, Hirschy, and McClendon, 2004). In their research on supportive campus environments, Kuh, Kinzie, Schuh, and Whitt (2010) note that:

> *"The conditions characterizing a supportive campus environment…include (1) an institutional emphasis on providing students the support they need for academic and social success, (2) positive working and social relationships among different groups, (3) help for students in coping with their non-academic responsibilities, and (4) high-quality student relationships with other students, faculty, and the institution's administrative personnel."* (p.241)

The methods to achieve these outcomes can include transition programs, advising networks, peer support, residential environments, multiple safety nets (including early alert systems), and special support networks for groups such as historically underserved students (Kuh et al., 2010).

Methodology

Model Characteristics

Previous research (Zhou et al. 2014) has shown that a student's first year of college is a vital time period for developing baseline knowledge, positive attitude, self-confidence, and commitment to college studying, which, in turn, establishes the foundation for the student's subsequent academic success including course grades, retention, and graduation on time. The first semester of college is especially important for first-time freshmen as they are faced with a variety of transitions from high school to college and therefore are at higher risk of withdrawal than students at later stages of their college career. Thus, predicting and identifying potentially at-risk students prior to the beginning of their college life would allow an institution to intervene effectively and would help more students successfully transition to college.

Using student data for the Fall 2012 and Fall 2013 new beginner undergraduate cohorts, an ordinary least squares (OLS) regression model was built to predict end of first semester cumulative GPA based on students' pre-college characteristics. The sample consisted of admissions data for 12,507 first-time students. The strongest predictor variables found in this study were high school profile information and standardized test scores:

- High school core GPA (unweighted high school GPA based on only core subject grades)
- Highest SAT verbal and math score (or converted ACT composite score)
- Highest SAT writing score (or converted ACT writing score)

In addition to academic predictors, students' demographic characteristics and background factors were also included in the regression model to control for background factors in order to derive accurate predictive weights associated with the academic factors (Geiser and Santelices, 2007). Omission of background factors may have led to significant overestimation of test scores and high school grades and thus biased conclusions. Demographic characteristics found to strongly correlate with first semester GPA are listed below in Table 2.

Table 2: *Demographic Characteristics*

Variable	Supporting Details
21st Century Scholar (TFCS)	Indiana's needs and performance based tuition program
First Generation	Self-reported, parents never enrolled in postsecondary education
Underrepresented minority (URM)	Self-reported, includes American Indian or Alaska Native, Black or African American, Hispanic or Latino, Native Hawaiian or Pacific Islander, and two or more races
Indiana resident	Binary, yes or no
Gender	Binary, Male or female

One predictor that was considered redundant and was not included in the model was student classification at the beginning of entry term, a binary variable for which 0 indicates a student entered the university with little or no credit and 1which indicates a student entered the university with 15 or more college credits. It was found that student classification and Indiana resident indicator were highly correlated. To avoid the collinearity and the noise it adds to the estimation, the resident indicator was kept and student classification was excluded.

For model validation, paired sample t-tests were conducted to compare the mean actual GPA and mean predicted GPA broken out by equal GPA intervals. Lift charts were also constructed in order to validate the model fit and to assess the predictive power of the model. Moreover, the response variable was transformed into a binary variable and a logistic regression model was built to further verify the model's accuracy.

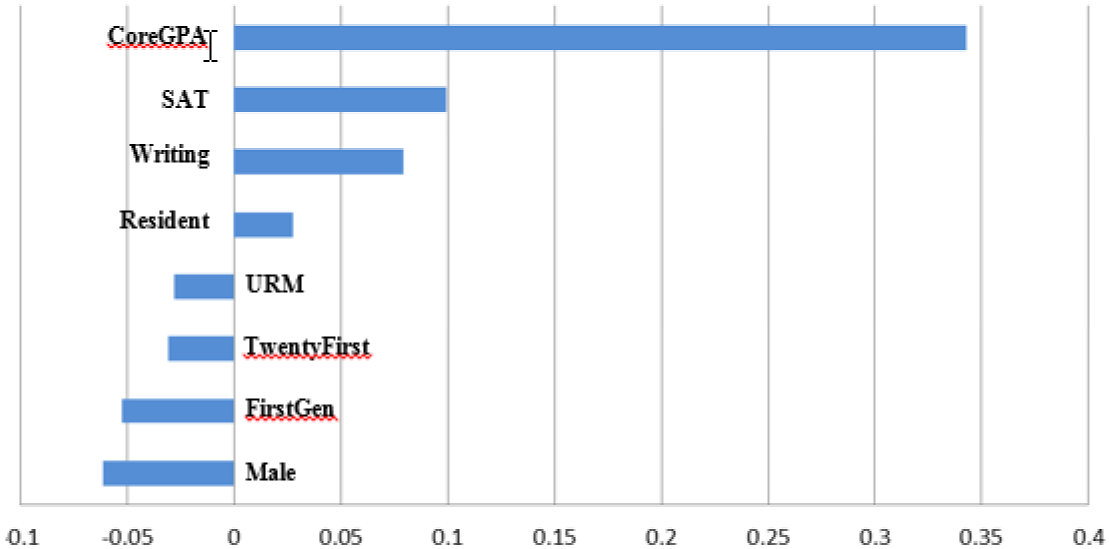
The model uses a cut point of 2.50 GPA or below to indicate a student is at-risk. In a study of long term retention, Singell and Waddell (2010) found that attriting students had lower first semester GPAs than students who graduate within five years or students who remained enrolled after five years. That initial GPA is slightly above 2.50 and falls in subsequent semesters. Additionally, Purdue University will enact a new probation policy in Fall 2015 where students who have less than a 2.00 GPA will be placed on probation. It was decided to use 2.50 to capture those students in the "murky middle" who would not automatically be on probation but would be close to doing so.

Model Fitting

In the regression model shown below, a strong relationship was found between cumulative GPA and each predictor at 1% significance level and the overall model was also statistically significant (overall F-statistics 388.17 with p-value <0.0001). Overall, 20.88% of the variation in cumulative GPA could be explained by differences in the predictors.

$$\begin{aligned} CumeGPA = {} & -0.2825 + 0.6734\, CoreGPA + 0.0005\, SAT + 0.0007\, Writ - 0.0925\, TwentyFirst \\ & - 0.0936\, FirstGen - 0.0747\, URM + 0.0420\, Resident - 0.0918\, Male \end{aligned}$$

Note that among the 12,507 total new beginners, 733 had missing predictors (i.e., SAT, Writ, and/or CoreGPA) and 98.23% of the 733 were students with foreign residency. Most of the missing predictors were SAT scores. To determine whether the mean cumulative GPA was the same for foreign and domestic students, a two-sample t-test was performed and the results indicated that there was a statistically significant difference between the mean cumulative GPAs for foreign students and domestic students (t=2.80, p=0.0051). In other words, foreign students tend to have lower mean cumulative GPA (2.9941) than domestic students (3.0561).



Note: all coefficients are statistically significant at 1% level and the overall model is statistically significant (overall F-statistics is 388.17, p-value<0.0001).

Figure 1: Standardized Coefficients for Cumulative GPA Model

To assess the predictive power of our model, lift charts were constructed. First, the data was sorted by predicted cumulative GPA from lowest to highest creating 20 buckets of equal number of students. Then the average actual GPA and average predicted GPA were calculated for each bucket, and both were plotted in a line chart. In the first lift chart below, there is an increasing trend of average actual GPA and tracking of predicted with actual values indicating a good model fit.

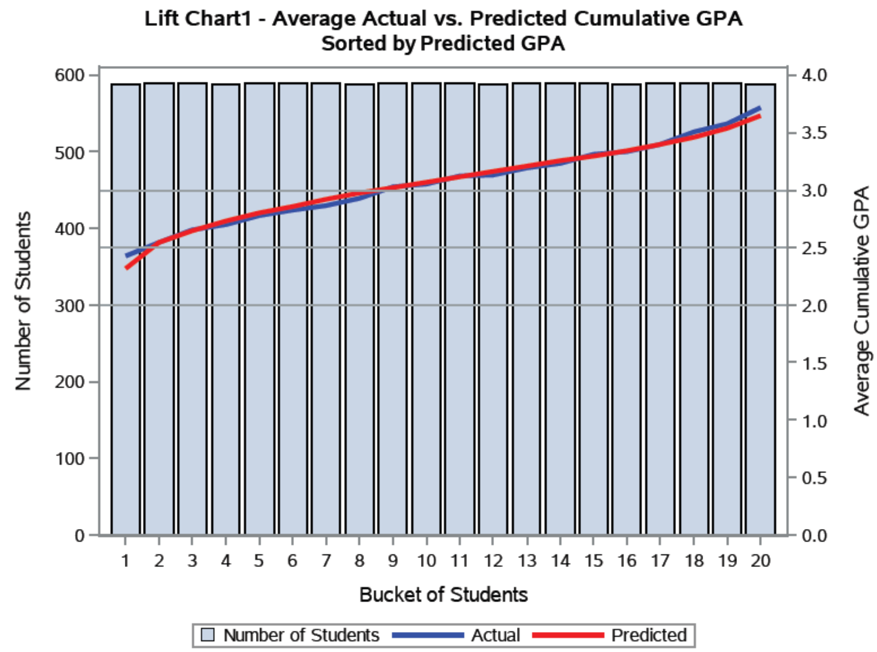


Figure 2: Lift chart 1

The second lift chart has an increased number of buckets at the lower end of predicted GPA – 10 buckets of equal number of students for the first 3% of students and 30 buckets of equal number of students for the remaining students thus focusing on the potentially at-risk students with predicted GPAs at the lower end. The model tends to under-predict the actual cumulative GPA of the lower end students, but does however predict who those at-risk students are.

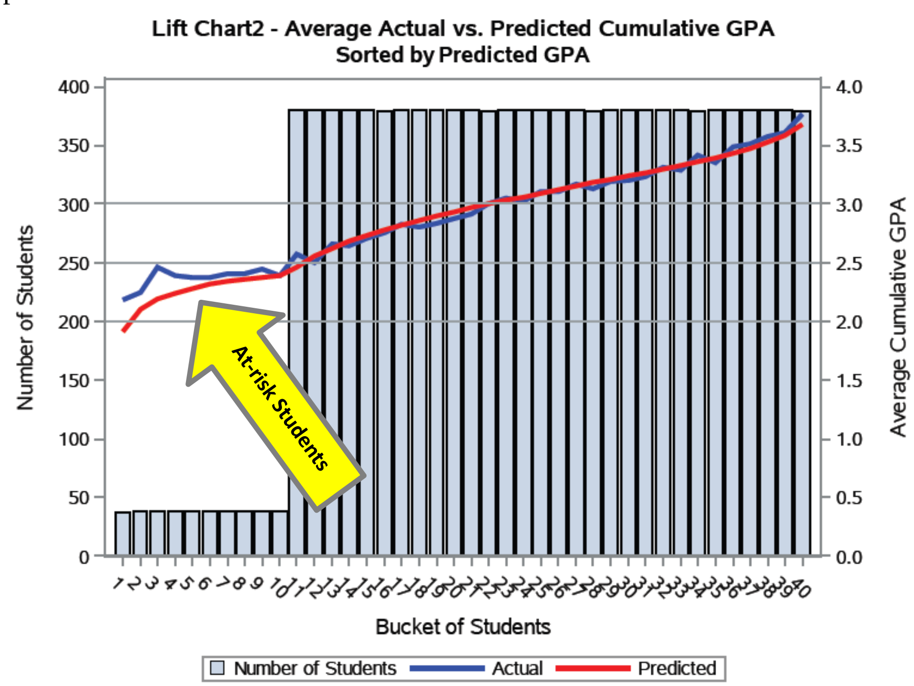


Figure 3: Lift chart 2

For testing purposes, the first-semester cumulative GPA was transformed into a binary variable using the cutoff point of 2.5 and a logit model was created based on the newly created binary outcome variable. The average of the predicted probabilities for having cumulative GPA over 2.5 was about 81% -- close to the actual frequency for having cumulative GPA over 2.5 (80.1%). The logit model correctly predicted 81% of the values and the rest were misclassified. The findings of logit model hint that although the model tends to over-predict students with low GPAs and under-predict students with high GPAs, it works well to identify potentially at-risk students if a student's predicted GPA determines her/his relative position among peers, instead of absolute GPA value. Table 3 illustrates the frequency of students at or below the 2.5 cutoff.

Table 3: *Binary At-Risk Indicator*

Cumulative GPA	Y codes	Frequency
>2.5	1	9539
<=2.5	0	2235

Results & Discussion

Based on the aforementioned model, 243 students in the incoming Fall 2104 cohort were predicted to have a GPA of 2.50 or lower. The predicted mean GPA of these students was 2.36 and the actual mean GPA earned after the conclusion of the semester was the same: 2.36. To further assess the variations in those students and their experiences during their first semester, we then examined the support interventions those students received as well as their individual course performance.

Support Interventions

Four student support programs were examined: 21st Century Scholars (TFCS) program, Purdue Promise, Horizons, and Supplemental Instruction (SI). The TFCS program assists students from low and moderate income families in Indiana afford their college education. Services provided to these students varies across the state but at Purdue it includes academic support in the form of free tutoring, career and academic counseling, professional and leadership development, and social support. Purdue Promise is open to Indiana residents who are low income and/or first generation and provides full tuition for their students, but the aid is tied to their participation in the program. Purdue Promise is a four-year support system comprised of coursework and highly intrusive coaching which focuses on academic, social, leadership, and life skills development. Horizons students must meet one of the following criteria: low income, first generation, or registered with the Disability Resource Center. It is available to non-Indiana residents as well. The Horizons program provides medium-scale support in the form of faculty and peer mentoring, academic and career counseling, free tutoring, and a designated work space for studying and computer usage. SI is open to all students and provides peer-led study sessions for high DFW courses.

Each student on the predicted at-risk list for Fall 2014 was given an additional binary variable of whether or not they participated in each of four interventions. Paired sample t-tests were then conducted to compare the predicted and actual cumulative GPA for participants and non-participants in each program. Table 4 shows the results of these t-tests.

Table 4: *T-Test Comparison of Predicted v. Actual GPA(Fall 2014)*

Grouping	N	Mean Predicted GPA	Mean Overall GPA
All Students	241[1]	2.36	2.36
Non TFCS Recipient	193	2.36	2.30
TFCS Recipient	48	2.35	2.59*
Non Purdue Promise	203	2.36	2.31

[1] Two predicted at-risk students did not register Fall 2014

Table 4: *T-Test Comparison of Predicted v. Actual GPA(Fall 2014)*

Purdue Promise	38	2.35	2.61*
Non Horizons	236	2.36	2.36
Horizons	5	2.40	2.29
Non SI Participants	215	2.36	2.32
SI Participants	26	2.36	2.67*

*Difference in means is significant at p<0.05

The GPA differences were significant for three of the four interventions: TFCS, Purdue Promise, and SI. All three of those interventions had higher than predicted GPAs. The non-participating students in each group had a mean actual GPA at or below the predicted mean. Pearson correlations (2-tailed) were run to compare the predicted GPAs to the actual term GPAs of the individual students in each indicated group, as seen in Table 5. Correlations were significant for All Students and for each of the non-participating groups. This again supports that the predicted GPA model holds true for students who do not have intervening academic and/or financial support.

Table 5: *Correlations of Predicted GPAs to Actual Overall GPAs (Fall 2014)*

	All	NonTFCS	TFCS	NonPuP	PuP	NonHrzn	Hrzn	NonSI	SI
All Students	.216**								
Non TFCS Recipient		.230**							
TFCS Recipient			.169						
Non Purdue Promise				.228**					
Purdue Promise					.157				
Non Horizons						.221**			
Horizons							-.767		
Non SI Participants								.240**	
SI Participants									-.076

**Correlation is significant at p<0.01

When broken down by number of Supplemental Instruction (SI) visits, none of the categories had statistically significant differences in means. However, 3-4 visits and 5-7 visits were close, both with a value of p=.08, shown in Table 6.

Table 6: *Predicted v. Actual GPA for SI Participants by Visit (Fall 2014)*

Grouping	**N**	**Mean Predicted GPA**	**Mean Overall GPA**
1-2 visits	11	2.33	2.51
3-4 visits	5	2.42	2.77
5-7 visits	7	2.38	2.84
8+ visits	3	2.31	2.74

Most students had no interventions, some had one intervention, and only a few had two interventions. No students had more than two interventions. The difference in means was significant at one intervention as shown in Table 7.

Table 7: *Predicted v. Actual GPA by Total Interventions (Fall 2014)*

Grouping	**N**	**Mean Predicted GPA**	**Mean Overall GPA**
0 interventions	166	2.36	2.26
1 intervention	69	2.36	2.57*
2 interventions	6	2.34	2.69

*Difference in means is significant at p<0.05

Course Performance

In additional to participation in intervention programs, we also evaluated at-risk students' performance in courses with high rates of D's, F's, and W's (withdrawn). We selected nine undergraduate courses that are commonly considered as first term critical courses. All of these courses have several hundred students enrolled each semester.

The comparisons of DFW rate between at-risk students and the rest of the cohort are shown below in Table 8. We can see that at-risk students had substantially higher DFW rates than the University DFW rates, indicating these students faced early challenges and struggled in the initial phase of college. This also supports the use of targeted intervention efforts that hopefully lead to improved outcomes and higher retention.

Table 8: *At-Risk Student Performance in High DFW Courses*

	Total At-Risk Enrolled	**DFW Grades**	**At-risk DFW Rate**	**University DFW Rate**
BIOL110: Fundamentals of Bio I	35	11	31.43%	14.85%
BIOL203: Human Anat & Physio	13	9	69.23%	19.94%
CHM115: General Chemistry	10	3	30%	8.04%
COM114: Fundamentals of Speech	82	17	20.73%	7.81%
ENGL106: First-Year Composition	107	18	16.82%	6%
MA153: Algebra And Trig I	69	53	76.81%	52.47%
MA158: Precalc Functions & Trig	57	19	33.33%	19.21%
MA161: Plane Analysis Geo Calc I	12	1	8.33%	10.73%
PHYS172: Modern Mechanics	3	3	100%	22.91%

Previous Cohort Retention

The final piece of the investigation was to look at those students from the Fall 2012 and 2013 cohorts and determine their university retention rates for the past two years. By retroactively applying the regression model, we were able to estimate at-risk populations for those cohorts as well, identified in Table 9.

Table 9: *Retention Rates by At-Risk & Non-Risk Categories*

Academic Year	**Cohort**	**N**	**One Year Retention Rate**	**Two Year Retention Rate**
2012-13**	At-risk	399	83.96%	74.94%
	Non At-risk	5930	91.48%	86.85%
2013-14**	At-risk	314	85.99%	
	Non At-risk	6005	92.97%	

**Difference in percentages is significant at p<0.01

In both cohorts, the retention rate for "at-risk" students was 7-12 percentage points lower than their peers. In Tables 10 and 11, similar differences were also apparent as the groups were subcategorized by gender and underrepresented minority status.

Table 10: *Retention Rates by At-Risk & Non-Risk Categories by Gender*

Academic Year	Cohort	Gender	N	One Year Retention Rate	Two Year Retention Rate
2012-13	Female**	At-risk	111	85.59%	76.58%
		Non-At-risk	2697	92.66%	88.25%
	Male**	At-risk	288	83.33%	74.31%
		Non-At-risk	3233	90.50%	85.68%
2013-14	Female	At-risk	95	91.58%	
		Non-At-risk	2650	93.43%	
	Male**	At-risk	219	83.56%	
		Non-At-risk	3355	92.61%	

**Difference in percentages is significant at p<0.01

Table 11: *Retention Rates by At-Risk & Non-Risk Categories by URM Status*

Academic Year	Cohort	Status	N	One Year Retention Rate	Two Year Retention Rate
2012-13	Non-URM**	At-risk	300	85.67%	77.67%
		Non-At-risk	5487	91.62%	87.15%
	URM**	At-risk	99	78.79%	66.67%
		Non-At-risk	443	89.84%	83.07%
2013-14	Non-URM**	At-risk	222	88.74%	
		Non-At-risk	5537	93.05%	
	URM**	At-risk	92	79.35%	
		Non-At-risk	468	92.09%	

**Difference in percentages is significant at p<0.01

With the exception of females in the 2013 cohort, all of the differences were statistically significant. Many groups were 10 percentage points or more lower than their colleagues. The starkest difference is for the 2012 at-risk URM students: by the end of their second year, only two-thirds of the original cohort remained, over 16 percentage points lower than their peers.

Conclusion & Next Steps

By using data from the Fall 2012 and 2013 cohorts, a reliable model has been developed to predict which incoming students are at-risk of not transitioning well to Purdue University. The model decently predicts the absolute value of a student's first semester GPA and can predict a student's relative position (above or below 2.50) at a rate of 81%. Student performance in critical courses and the improved performance of students who receive targeted interventions support the model as well. Structured programs for changing their behaviors and providing them with needed academic and social supports make a difference in first semester student performance.

Next steps for improving the at-risk model include the addition of other predictors such as student study habits in high school and TOEFL scores to the regression model and the creation of interaction terms among new and existing predictors (e.g., SAT x residency). It would also be of interest to refit the model based on subgroups of interest – for example, domestic versus international students or by entry college. Students in the Exploratory Studies Program (undecided students) and the College of Liberal Arts are highly overrepresented on the at-risk list. Purdue also has a steadily increasing international population, most of whom are excluded from the model due to lack of SAT/ACT test scores. There is also a need to build a model for predicting at-risk of probationary students beyond the first year.

In terms of implementation, this model will be used again to predict the at-risk students for Fall 2015. Efforts are already underway to expand some of these existing programs to allow more students access to these resources. A task force has been formed to communicate these findings and help different campus departments collaborate with each other. Further steps also include identifying other interventions across campus (College of Science Help desks, Minority Engineering Program, etc.) and measuring the success of students who utilize those resources. A pilot program is being proposed with the College of Liberal Arts and Exploratory Studies (undecided students) to appoint specific academic advisors for the predicted at-risk students. With time, we hope these efforts will increase student retention and graduation rates and in turn, increase student success.

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