composite with a minimum ACT English subscore of 17 and ACT mathematics subscore of 17. Additionally, students are required to have completed the college preparatory high school curriculum (Valdosta State University, 2013).

1. At-risk general: VSU postulates that there is a relationship in the variables of standardized test scores, high school grade point average, and high school curriculum rigor and performance to predict college retention.
2. At-risk mathematics-based courses:

examined and assigned point values based on the percentage of students who passed and those who exceeded the expectations of the graduation and performance tests. The schools with higher percentage of students who exceeded the test expectation were given a higher point value. The total points were placed into four categories or quartiles. Students who came from a non-Georgia public high school, or a Georgia public high school with too few students were given a null category. The top quartile is given a value of one, while the bottom quartile is given a value of four. This component, like the standardized test scores and high school grade point averages, are on a rolling basis where each year the quartiles ranges are reevaluated to adjust to the changes in the academic success of students.

Explanation of the At-risk Coding

With the high school curriculum rigor and performance, the high school grade point average, and the standardized test scores tiers, the results yielded 80 different combinations. Tier value of 1 means the top, while tier value 4 means the bottom. A student’s code would look like the following: 3-1-4. The first number would be for the high school curriculum rigor and performance, the second number would be for the high school grade point average, and the last number would l-4<0051 0 0f31 4(m)17(anc)8(e)]TJETzed testh-4(sc)7(o

the actual and predicted retention rates, any combination that has an actual or predicted rate of 65.0% or lower was flagged as at-risk for retaining to the university.

At-risk Mathematics-based Courses

Like the at-risk general, the at-risk mathematics-based courses have a total of 80 different combinations. A test of the full model against a constant only model was statistically significant, indicating that the predictors as a reliable set to determine the probability of students passing a mathematics-based courses at the university (χ^2=1641.501, *df*=3, *p*<.001). The constant is significant (β_0=2.794, df=1, p<.001), the high school curriculum rigor and performance was not significant (β_1=-0.007, df=1, p<.359), the high school grade point average was significant (β_2=-0.608, df=1, p<.001), and the standardized test scores was significant (β_3=-0.270, df=1, p<.001). While the high school curriculum rigor and performance was not significant, the overall model was significant. Using the following equation from above, students with a 1-2-3 would have a mathematics-based course pass rate probability of 68.2%, while students with 4-4-4 have a 32.2% pass rate. Within the actual and predicted pass rates, any combination that has an actual or predicted rate of 65.0% or lower was flagged as at-risk for failure in a mathematics-based course at the university.

At-risk Reading-based Courses

With the 80 different combinations, a test of the full model against a constant only model was statistically significant, indicating that the predictors as a reliable set to determine the probability of students passing a reading-based course at the university (χ^2=1641.501, *df*=3, *p*<.001). The constant is significant (β_0=3.083, df=1, p<.001), the high school curriculum rigor and performance was significant (β_1=-0.012, df=1, p=.030), the high school grade point average was significant (β_2=-0.555, df=1, p<.001), and the standardized test scores was significant (β_3=-0.111, df=1, p<.001). Using the following equation from above, students with a 1-2-1, they would have reading-based pass probability of 86.4%, while 4-4-4 students have a 59.2% pass rate. Within the actual and predicted pass rates, any combination that has an actual or predicted rate of 65.0% or lower was flagged as at-risk for failure in a reading-based course at the university.

Implementation and Results

With the predictive analytics developed to provide information about the entering students to faculty, a portal, called Valdosta State University Faculty portal, was launched in August 2012. The faculty portal provides faculty with information on students who are enrolled in their courses and it also provides information on faculty advisevi9-3(m)17(TJETBT)9(r)-3(se)-3

Over the course of the academic year 2012-2013, the data collected by the portal was analyzed, especially focusing on the faculty who had a high number of at-risk students enrolled in their courses. Largely, this was the Department of Mathematics and Computer Sciences. Table 12 shows the crosstabulation of the pass rates by faculty views. The threshold was set at least 100 views for improvement to occur. Pass rates of faculty who had 100 views or more had a 6.3% higher pass rate than those who had less than 100 views. In order to determine if the increased pass rates were statistically significant, a chi-square test for independence was conducted. The relation was significantly different, $\chi^2(1, N=7,475)=28.097$, $p<.001$. The size effect, Cramer's V, is a weak relationship, .061. This means that students who had a faculty who had at least 100 views in the portal are more likely to have higher pass rates than students who had a faculty who had less than 100 views.

Table 12: Crosstabulation of Pass Rates by Faculty Page Views

Additionally, the flag set by a faculty member would potentially show faculty's intentions of helping a student to succeed in the course. The threshold was set at a minimum of five flags. Table 13 shows the crosstabulation of pass rates by the faculty who set at least a minimum of five flags. Of the faculty who set at least five flags, the pass rate is 10.2% higher than the pass rates of the faculty who set fewer than five flags. In order to determine if the increase in pass rates was statistically significant, a chi-

Conclusion

Overall the data gathered from developing predictive analytics and implementing a portal system that was utilized by VSU's faculty shows that these interventions have helped students succeed in their academic careers at VSU. Moreover as a result of the success of the portal, the information was distributed to advisors and teaching faculty so that they become more aware of the abilities and possible struggles of the students they advise and teach in their courses.

Essentially the predictive analytics and the portal take a more proactive role in student success and intervention strategies. When faculty members log into the portal and select courses for which they are teaching, they will see their student roster with pictures of their students and indicators if the student is at-risk in any of the three areas. This portal system has been integrated with our advising software, DegreeWorks, so faculty advisors will have a better understanding of their advisees and their likelihood to struggle with certain coursework. Faculty also have the ability to flag a student who is struggling within their course, regardless of whether the student is at-risk or not, and by flagging the student a series of automated communications to academic and student support services will be generated so that a proactive approach to tutoring in student success can be made by the institution.

As a result of the improvements made from predictive analytics, VSU has begun to research advanced math at-risk where it identifies a student who will be more likely to struggle with advanced mathematics courses and new at-risk indicators for when students successfully reach 30 credit hours.

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