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Towards Early Identification of Engineering Students at Risk for Academic Danger

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Introduction and Background

This research paper describes the development and validation of an early-identification system for detecting students at risk for academic action (probation or suspension) after their first semester. The College of Engineering at Ohio Northern University has grown significantly over the past 5 years, which has placed strain on limited academic support resources for these students. To maximize the use of these limited academic support resources, it is important to connect these resources to students who need them most.

Academic support services include one-on-one tutoring in writing and specific coursework, accessibility services for students with disabilities, supports for international students, and help with resumes and job prospects, among other services centralized at the university's Center for Student Success. Aside from connecting students to these services, faculty support at-risk individuals informally with impromptu office hours meetings, or more formally with a "Student Development Plan" (this latter intervention, formerly called a "Student Improvement Plan," was recently reimagined to focus on students' strengths rather than their deficits; see [1]). A newer intervention includes chatbot text messaging with our school mascot, intended to remind students about on-campus resources.

A key challenge with promoting these resources is balancing staff availability with students who truly need support. While attending tutoring sessions may be more-or-less beneficial for all students, this would overwhelm our limited number of tutors. On the other hand, relying solely on the list of students placed on academic probation would be ineffective because interventions would not take place until after the first semester. Supporting students too late can add additional pressures, since low GPAs can affect federal aid. Students may also face threat of academic suspension if their GPA remains low (typically less than 1.0, though historically, students with GPAs under 1.5 during their first semester do not succeed in our engineering program). Out of average cohort sizes of around 200 students, about 11 first-year students are placed on probation or suspension. This study defines at-risk students as those who are likely to be placed on academic action (GPA less than 2.0) at the end of their first semester.

Successful early interventions can include any of the three outcomes:

1. Ideally, a student improves their GPA before the end of the semester
2. A student's following semester (possibly including a J-term course) is strong, significantly improving their GPA
3. A student opts for a more appropriate major within the university, given their interest and skillset

The idea of predicting student academic success using statistical or machine learning methods is not new. However, as with all approaches, institutional context matters, as does the data which are used to make the prediction. Previous studies have shown that high school GPA and standardized testing are not reliable predictors of academic success in the transition from high school to college [2-4]. Processes using these inputs have become further complicated in recent years by test-optional admissions policies and weighted GPAs. Some studies found that class rank or performance in high school math and science courses were better predictors [5, 6]. In addition to prior performance, some studies use demographic data, personality traits, or other metadata to make a prediction of student success [7, 8].

While these studies generated models with predictive power in their context, the use of admissions data or profiling can impact faculty and staff perception of students entering engineering programs. Instead of relying on pre-enrollment data, some studies focus on student data once they are enrolled as their input. Some studies combine pre-enrollment data with academic analytics data once students are on campus [9]. Other studies have applied data mining and machine learning techniques to predict student performance at the course level based on student engagement with online course content and learning management systems [10, 11]. Another approach is to use exam grades, homework assignments, and in-class participation to predict student performance in courses [12]. Course grades in first semester foundational courses or several semesters of courses have also been used to similar effect [13, 14].

All of these studies have limitations for the application described in this work. Models based on pre-enrollment data are likely to label students as at-risk before they have arrived on campus, and will miss highly-qualified students who struggle to adjust to college life. Models that predict performance in a single course are not broad enough to catch students at-risk for academic action. Studies that use semester grades or several semesters of course grades may identify students too late to make a meaningful change to their progression or academic habits.

The approach detailed below attempts to identify and serve as many students at risk for academic action as early as possible, while optimizing limited student success resources. There are several pertinent metrics to evaluate the success of this approach. The first is classification accuracy, defined as the proportion of correctly classified predictions. In datasets where one class is dominant, model accuracy can be misleading. The true positive rate (TPR) is the proportion of correctly identified positives to ground truth positives. False negative rate (FNR) is 1-TPR, and describes how often the model fails to catch a true positive. False positive rate (FPR) is calculated as the proportion of ground truth negatives that are incorrectly classified to be positive [15]. The data in this research is dominated by students who were not at-risk for academic action, so classification accuracy is a poor metric. The ideal model needed for early identification should maximize TPR, which also minimizes FNR. More succinctly, we wish to correctly identify students in need of additional support while avoiding overtaxing our student success resources, and so an additional design objective is to keep FPR small. Data to inform this model will be pulled early enough in the first semester for substantive intervention before students end up on academic probation or suspension.

Approach

Ideally, data used in forming a predictive model for early identification of at-risk students should be:

- Easily accessible so as to not require much additional work for student support staff
- Historically tracked to provide training data for the model
- A small enough set of inputs to provide reasonable accuracy early enough in the first semester to enact meaningful student success interventions

Based on these requirements, four inputs were selected:

1. The specific math course in which each student is enrolled
2. Midterm grades for the first-year engineering design course
3. Midterm grades for first semester mathematics courses
4. "Professionalism expectation" scores in the same first-year engineering design course during the first five weeks of the semester

Professionalism expectations in the first-year engineering design course include attendance and brief student tasks. These tasks include, for example, adding their headshot and biographical information to their class's picture roster, making a reservation with the Writing Center, and completing teammate evaluation surveys after each project. These tasks are not graded in the traditional sense; instead, students are docked points if they do not complete these tasks by their respective deadlines. Professional expectation scores make up about 10% of students' grades in the first-year design course, and are intended to hold each individual accountable to a high standard. Students earning low professional expectation scores are contacted by their instructors and invited to meet during office hours to discuss organizational and time management skills. Anecdotally, about half of the contacted students take up this offer.

Historically, midterm grades have also been used as inputs to identify at-risk students. For example, faculty advisors may be aware of midterm grades during the advising period, providing an opportunity to speak with students about their progress. While these types of interventions may be helpful, these approaches are ad-hoc, and do not necessarily involve the staff members who could formalize support strategies.

Data

To train and validate the model, historical data have been collected over three successive fall semesters (2021-2023). In addition, term GPAs, which link to academic actions of probation or suspension, were collected. These data are used to assess the following research question:

RQ: *To what extent do the proposed factors validly predict which students will be at-risk for academic action?*

This work will discuss the principal results from this early identification study and will describe intervention strategies for students identified as at-risk through application of this analysis. Important metrics for determining the accuracy of this analysis include:

1. What percentage of students are correctly identified as at-risk for academic action?
2. How many false positives or false negatives are identified?

In this study, only one machine learning approach was applied. Logistic regression was chosen because at-risk status is a binary outcome [16]. The aim of this work is not about exploring the particulars of machine learning and modeling but is rather about effectively supporting student success.

After data cleaning and preparation, the dataset contains 379 entries across three years of data. Of this dataset, only 33 entries are true positives (indicating a student as at-risk).

Results

Using a logistic regression model, the primary parameter to tune is the decision threshold. The primary objective was to maximize the TPR and minimize TNR, prioritizing the identification of all students who may be at-risk even at the cost of some false positives. This objective reflects that failing to identify an at-risk student represents a missed opportunity for timely intervention and support, whereas a false positive simply results in offering support to a student who may not ultimately need it. A secondary objective is to also keep the FPR relatively small, to avoid overwhelming student support staff and ensure those who require the most intervention are well supported.

Figure 1 shows the TPR, FNR, and FPR for the model under different thresholds. While 0.2 maximizes TPR and FNR, the secondary objective of keeping FPR small was a key tradeoff. At a threshold of 0.2, an equal number of students were falsely classified as ‘at-risk’ as were correctly identified. To avoid overwhelming student support resources, the threshold of 0.3 was chosen because it balanced the tradeoff best. While TPR dipped only slightly by moving from 0.2 to 0.3 (5%), the FPR decreased by nearly a factor of 2.

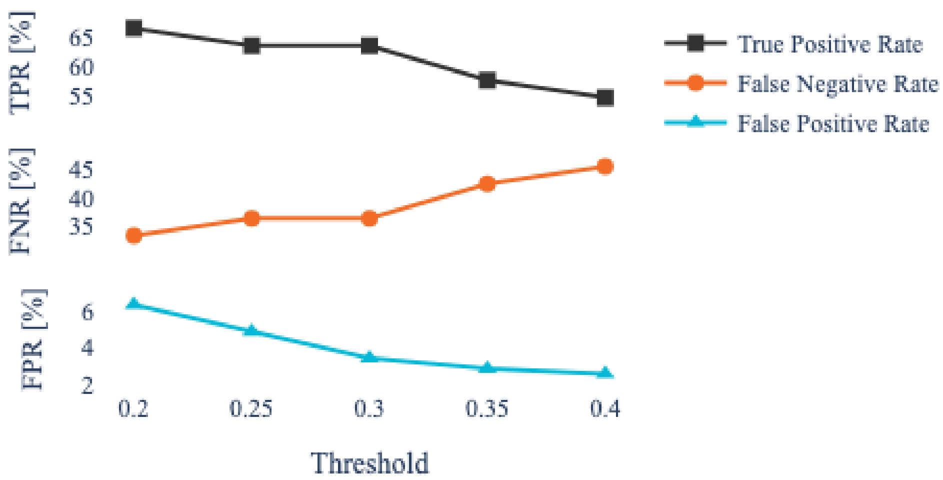

Figure 1. TPR, FNR, and FPR over different logistic regression thresholds

Five-fold cross validation was used to validate the model described in this work. Table 1 presents the results of a logistic regression model. The only effect that was not statistically significant was the first-year design course professional expectation points. Students starting in Calculus 2 (53 data points) or Pre-Calculus (44 data points) were more likely to be at-risk for academic action than students starting in Calculus 1 (250 data points). Logically, a higher math midterm GPA and engineering midterm GPA results in students being less at-risk.

Table 2 shows the confusion matrix for the logistic regression model after five-fold cross validation with a threshold of 0.3. For this model, the overall model accuracy was 93.7%. This high accuracy is misleading since only 8.7% of the students in the data set were truly at-risk of academic action - so a model that classifies all students as 'not-at-risk' would result in an accuracy of 91.3%. It is more pertinent to look at the TPR, which was 63.6% (21/33 classified correctly as at-risk). The FNR was 36.4%, while the FPR was only 3.5%.

Discussion and Future Work

As described in this study, there is a careful balance at hand between pushing down false positives (intervening when not needed) and false negatives (missing a needed intervention). If more resources become available, the threshold could be tuned to err more on the side of false positives. The risk of harm in these cases is minimal - borderline students will be bolstered, and the additional resources would be used to push up a student who was likely to have succeeded on their own. Such a change in threshold would likely also reduce false negatives, meaning additional at-risk students could be supported. Some identity risk may be present if the intervention is not framed correctly, but the contents and means of intervention are beyond the scope of this work.

Table 1. Logistic regression model for at-risk status for first-semester engineering students

	Coefficient	*Odds Ratio*	*95% CI*	*p*
Calculus 1 Start	2.81	12.6	[0.87, 4.8]	0.0045
Calculus 2 Start	4.14	63.3	[1.9, 6.4]	0.0003
Pre-Calculus Start	4.42	83.1	[2.1, 6.7]	0.0002
Advanced Math Start	3.99	54.3	[1.6, 6.4]	0.0013
Engineering Midterm GPA	-0.984	0.37	[-1.47, -0.50]	0.0001
Math Midterm GPA	-0.833	0.43	[-1.22, -0.45]	<0.0001
PE Weeks 1-5	-0.055	0.94	[-0.12, 0.01]	0.0855
				Pseudo R^2=0.471

Table 2. Confusion matrix for five-fold cross validation of the logistic regression model with a threshold of 0.3

	Classified Negative	Classified Positive
Ground Truth Negative	334	12
Ground Truth Positive	12	21

Conversely, in an environment of more limited resources, the minimization of false positives may be the more optimal objective. This is as seen in the analysis above, where roughly a third of struggling students were missed but only a small fraction of otherwise succeeding students were flagged. The risk here is that students who are likely to leave the program are left to do so without intervention. From a systemic perspective, the baseline comparison is 100% of at-risk students leaving the program and thus any intervention that lowers that number is a positive for the institution, especially given the compounding effect of early intervention. For this reason, optimizing the use of resources, even at the risk of not catching 100% of at-risk students, is deemed the better solution path.

One benefit of the analysis of at-risk status presented in this work is that it provides some opportunities for deeper discussion. In prior internal studies, the Professional Expectations score from the first-year design course was shown to be a highly relevant factor in student persistence. For that reason, the practice of ad-hoc instructor outreach was initiated. The fact that it is not appearing as relevant in these models may indicate that the previously established intervention is successfully catching a large percentage of those students at-risk for organizational/attitudinal reasons. On the other hand, it may instead indicate that this factor has become less important to the retention of students. Without additional data, such as a control population in which the instructor does not reach out to these students, it is unclear which interpretation is correct.

The midterm grade measures are seen to be highly significant but of lesser importance to the model (lower coefficients) than the math course in which a student starts. This emphasizes the importance of midterm grade reporting, supporting an institutional push to collect this dataset, but also supports the case that midterm grades alone are an insufficient indicator of at-risk status. The engineering midterm GPA in particular is largely dependent on the one first-year design course which, at that stage in the term, has only a few assignments returned and none of the major design projects which make up the bulk of the course. It might be of interest to rerun this study with a later grade marker from this course, to see if a slightly delayed risk analysis or an adjustment to that course's schedule might provide a stronger predictive tool for risk intervention. It should also be noted that [this institution] does not use a plus/minus grading scheme, meaning that grade reporting and, by extension, GPA, is a very coarse measure. An institution that has more fidelity in this measure may find that it weights more highly in their risk model.

The high weighting of math placement bears additional exploration. The markedly high odds of a student starting in Pre-Calc landing on the at-risk list is logically understandable; these students are less prepared in foundational mathematics and are often less likely to have taken high school physics and/or chemistry courses, leading to greater difficulty in those areas as well. Conversely, the fact that taking Pre-Calc doesn't seem to be enabling these students to overcome those risk factors is a concern that demands investigation. Do these figures indicate that there is a broader risk factor surrounding these students that is not being addressed by the remedial math content? Or is the course not sufficiently addressing the math remediation and thus there is a need to rework how this course is delivered? If this is found to be the case, it may demand institutional reform to seek alternative models for supporting and teaching students with lower math preparation in high school. An interesting comparison point would be to examine only those students who were placed into Pre-Calc but opted into Calc 1, to explore the comparative rates at which they appear on the at-risk list versus those who remained in Pre-Calc.

More interesting is the fact that students starting in advanced mathematics (Calc 2 and beyond) are at higher risk than those starting at Calc 1. Some of this may be attributed to the overconfidence effect. Students come in imagining their preparation to be stronger than it is in reality, struggle to succeed in a course for which they are not truly prepared, and that struggle bleeds into other courses and, perhaps, a general identity crisis on the part of the student. Two paths open from this finding. Students in this situation may find themselves less connected to their peers since they are not in the same math course as the vast majority of their cohort. Perhaps some broader identity and cohort building around this group would help shore up the related risk factors. Secondly, it reinforces the advice given to most incoming students when considering their math placement - to retake the highest level math for which they were granted credit. For example, a student with AP credit for Calc 1 is advised to retake Calc 1, rather than advance to Calc 2. This “half step back” approach ensures that students are able to reinforce foundational content before moving into more difficult courses. Based on the results of this study, perhaps this consideration should be made stronger or even the default pre-registration path. Alternatively, perhaps additional support structures are needed here. It could be reasoned that students in these advanced courses who land on the at-risk list are likely talented individuals, yet they may struggle to navigate the transition from a high school curriculum in which they were not challenged to a collegiate environment where a great degree of academic maturity is needed. Additional interventions may help these students better navigate this change and lower these risk odds. While there are other factors at play that make allowing advanced math placement necessary, the fact that it is roughly a coin toss as to whether those students succeed or not is extremely curious and should give pause to those wanting to accelerate their math sequence without additional support. Conversely, consistent with the broader conversation in the engineering education community, it begs the question of why success in upper level mathematics is so critical to success in engineering studies.

Conclusion

This study successfully developed and validated a localized early-identification system to detect first-year engineering students at risk for academic action. By utilizing data readily available within the first five to eight weeks of the semester (specifically math placement, midterm grades in engineering design and mathematics, and early professionalism scores) the college can now identify roughly 64% of at-risk students before the first semester concludes.

The findings underscore three critical insights:

- The Predictive Power of Placement: Contrary to the assumption that advanced placement leads to smoother transitions, students starting in Calculus 2 or higher faced significantly higher risks than those in Calculus 1, suggesting a "gap" in academic maturity or peer cohort integration that requires targeted support.
- The Trade-off of Resource Allocation: By selecting a decision threshold of 0.3, the model achieved a high level of specificity (96.5%), ensuring that limited student success resources are not diluted by an unmanageable number of false positives, while still capturing the majority of students in need. Depending on the resource context of other institutions, that threshold may bear adjustment to allow higher capture of true positives at cost of higher false positives and resource dilution.

- Actionable Mid-Semester Data: The significance of midterm grades validates the institutional push for early grade reporting, proving that even "coarse" grading data provides a superior intervention window compared to end-of-semester post-mortems.

While the "Professionalism Expectations" metric did not reach statistical significance in this specific model, its previous success as an ad-hoc intervention suggests that the college's existing proactive outreach may already be mitigating the very risks the model seeks to measure.

Future iterations of this work will explore whether adjusting the timing of design course markers or refining math placement advising can further reduce the false negative rate, ensuring that no student's struggle goes unnoticed during the critical first-semester transition. Additional factors may also be explored, such as student demographics.

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