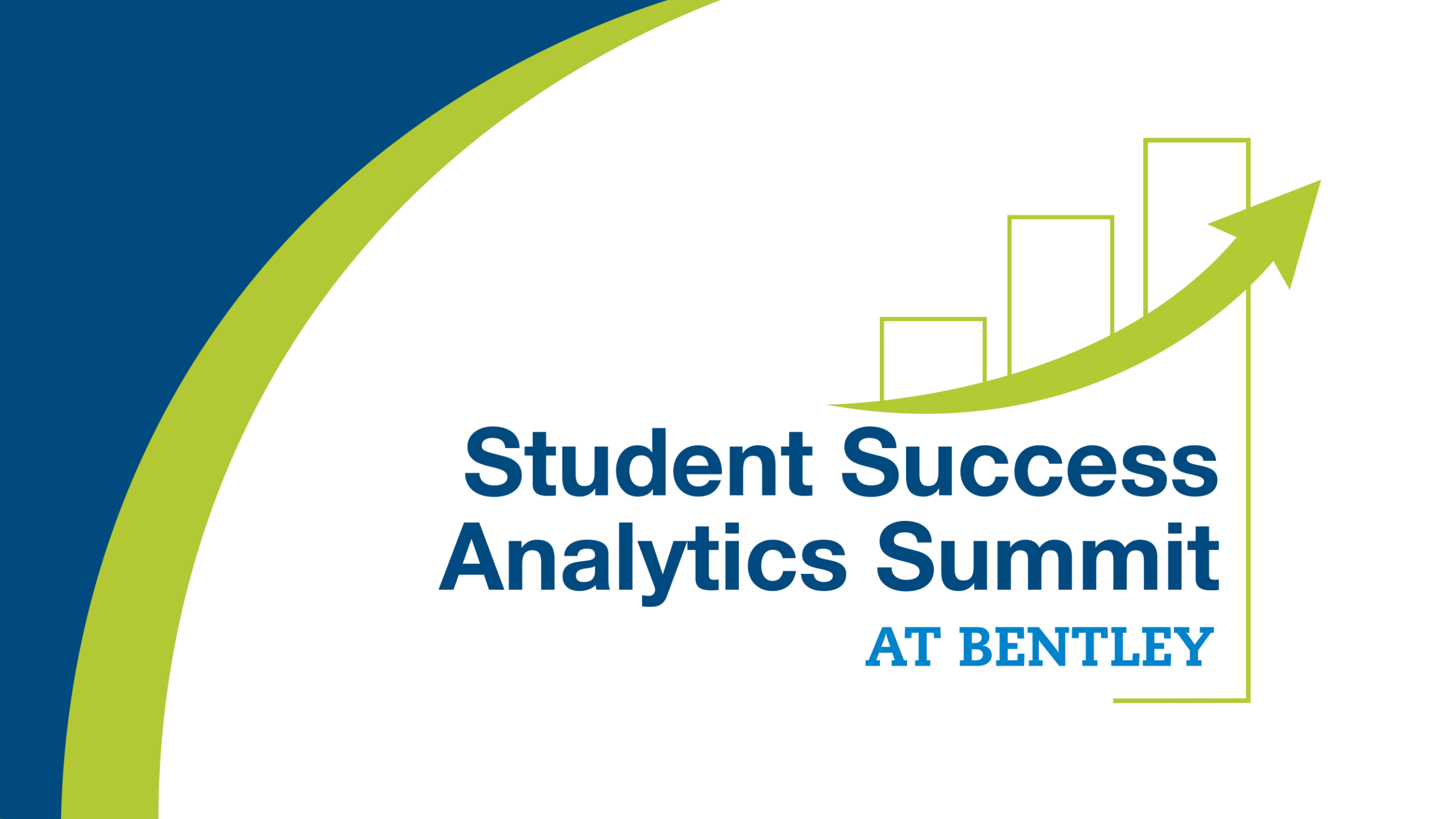




Student Success Analytics Summit

AT BENTLEY

Bentley's First Predictive Model for Student Success

Nathan Carter, Director, Center for Analytics and Data Science (CADS)

Gabrielle Friedman, Business Systems and Data Analyst, IT

Rahat Sabymbekov, Data Scientist, Office of Student Success (OSS)

Gregory Vaughan, Chair, Mathematical Sciences Department



Outline



1. Project origins
(Fall 2025)

Nathan Carter



3. Difficulties
encountered

Rahat Sabyrbekov



2. Expanding the
team (Spring 2026)

Greg Vaughan



4. Results and
future work

Gabrielle Friedman

5. Discussion

Things you can look forward to

Lessons we learned



Activities

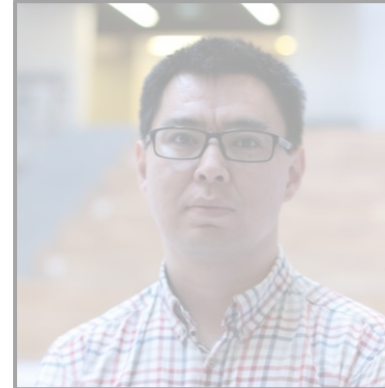


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Problem origins



Jane De Leon Griffin
Associate Provost, Student Success
Professor, Modern Languages

Conversation in 2025 about collaborations between CADS and OSS

- CADS seeking internal consulting
- OSS eager to get more data-driven

Resources OSS already had:

- Jane's position and mandate
- BaSSE project, including goals and funding
- New data scientist on team, Rahat
- Descriptive analytics dashboards

Problem statement

- Student attrition often becomes visible when it's already too late
- Can we augment our existing tools with early risk signals?



- Bentley's First Predictive Model for Student Success

Feasibility Study

- First predictive goal:
Which students are on-track to graduate in four years?
- **Does OSS already have access to any variables that are correlated with graduating in four years?**
- Brought Greg Vaughan into the project
 - Statistics expertise
 - Department chair experience
- Answer: Yes, there are useful predictors, such as:
 - ACAD score
 - Grades in GHEFY courses

Lessons Learned

1. On-campus partnerships have a lot of benefits

- Leveraging existing expertise
- Making new connections
- Using existing institutional knowledge

2. Feasibility checks are worth it

- 5% of the cost of the whole project
- Gave us confidence to proceed

Moving to the next phase

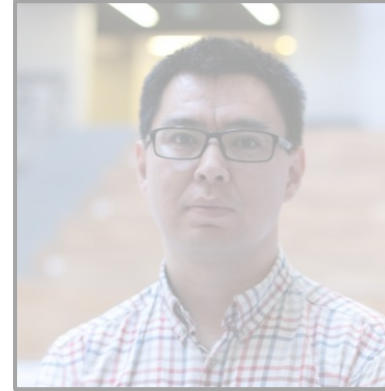
- The feasibility study said to proceed.
- **Goal for the full project:**
 - Create a dashboard for advisors
 - Alert them to which students are at risk for not graduating in four years
 - Advisors can then reach out with extra support

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Identifying Tasks and Team

- Final Product: Dashboard
 - Data Analyst with PowerBI Expertise
- *Interpretable* Predictive Model under the hood
 - Statistician to perform model building and assessment
- Data Pipeline to Feed Model and Dashboard
 - Data Scientist (or two!) to build, refine, and maintain pipeline
- Optimize user experience
 - Experience Design team to identify optimal setup via end users

Full Team – Met every Thursday at 8:30

- **Data sourcing and oversight**

- Steve Cross
- Leela Munagapati
- Rachel Penn
- Annie Raunikar
- Edlira Stefani

- **Data cleaning and modeling**

- Nathan Carter
- Gabrielle Friedman
- Rahat Sabyrbekov
- Greg Vaughan

- **User Experience**

- Chris Haas
- Jason Reynolds
- Atharv Wairagade
- Peter Xu
- Daisy Yin

- **Project Leads**

- Greg Coco
- Jane Griffin

Defining Goals

- What do we mean when by predicting “student success?”
 - We debated between graduate in 4 years or 6 years.
- We ultimately settled on graduating in 4 years for two main reasons
 - An overwhelming majority of Bentley student graduate in 4, so looking at graduating in 6 years wouldn't change much.
 - We realistically had complete data for ~10 cohorts using grad in 4 years; using grad in 6 years would have reduced that by 20%.
- With this binary dependent variable, we used logistic regression

Defining Goals: One More Step

- Okay, we are modeling the *probability of graduating in 4 (PG4)*! ...but how does *when* we are making predictions play a role?
- Our ability to predict if someone will graduate in 4 will be different when they are Freshmen vs. Seniors
- **Our Solution: Different models for different points in time**
 - Model 1: predict PG4 before first semester
 - Model 2: predict PG4 after first semester
 - Model 3: predict PG4 after second semester
 - ...
 - Model 8: predict PG4 after seventh semester

Identifying Predictors

- With this set up, we would look at the value of predictors at each given point in time for each respective model
- The variables we used came in two main categories
 - Academic performance
 - Cumulative GPA
 - Cumulative credits
 - Final Grades in a variety of foundational courses required for all students
 - Demographic
 - First Generation status
 - HS Academic (ACAD) score
 - Start semester

Activity 1

- There is a tension between the variables we want and those we have.
- Let's first consider the variables you want.
 1. **What variables would you consider ideal for predicting student success at your institution?**
 2. **Are there other measures of success you want to predict?**

Activity 1

- Some variables we wanted to include (but ultimately weren't able to):
 - Course level data such as homework or exam grades
 - LMS activity data
 - Progress reporting data

The Road Not Taken

- Some predictors we had to weigh against other factors
- Race and gender might have improved performance, but there were concerns about unintended implications.
 - E.g., “Student X is less likely to succeed because they are of race Y”
- We felt that any potential benefit these metrics would have brought could be gained in other places:
 - ACAD score
 - Initial college academic performance

Activity 2

- **Thinking back to the ideal metrics you identified in Activity 1, are there any complications that might make them difficult to use?**
- **Are there any alternatives at your institution that might “make up” for these if they weren’t included?**

Lessons Learned

1. Alternate ideating and exploring

- It can be alluring to dream big, but building a model is an iterative process

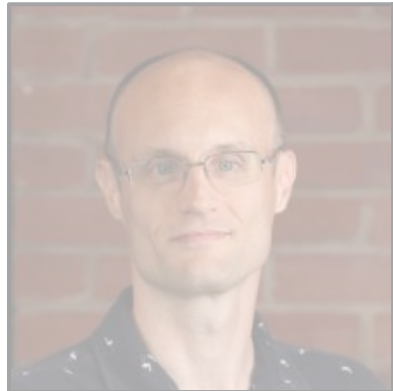
2. Be precise in your goals

- "Predicting success" can cover a wide range
- Be clear about what you want to predict and when you want to predict it to help keep scope manageable

3. Don't be afraid to start small

- Done is better than perfect
- If you don't get everything in on the first attempt, once a model is built, it will be easier to add to later

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Difficulties of various forms



**DIFFICULT
DEFINITIONS**

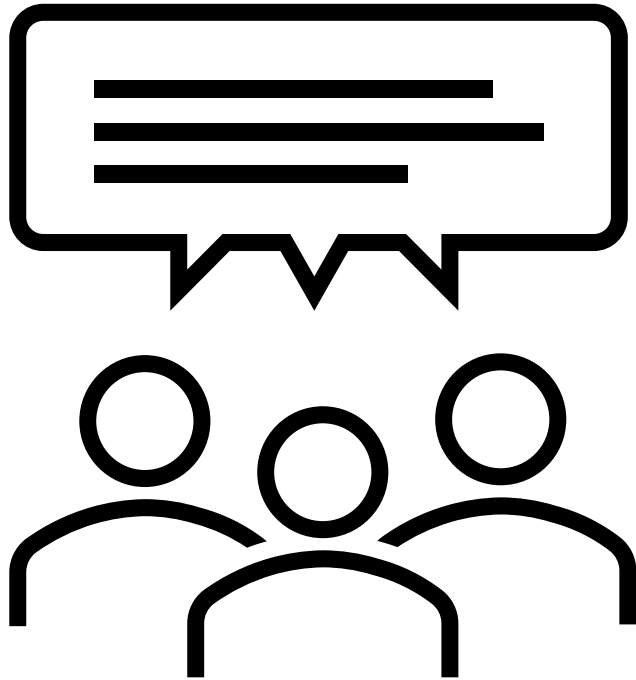


**LOGISTICAL
CHALLENGES**



DATA QUALITY

Difficult definitions



Edge cases like stop-outs must be defined before the training population can be set.

Learn and follow the established institutional definitions (e.g. GHEFY, ACAD score).

Counting "semesters" are complicated by summer and winter terms - > 'halves'.

Combined BS/MS programs resist a single definition of success.

The most predictive grade cutoff was not always DFW — sometimes it fell between B/C or A/B.

D, F, W – may indicate different scenarios of student learning

Logistical challenges



Direct database queries were slow, so a cloud pipeline now stages the relevant data for efficiency.



Reusing existing data views saves time but risks outdated or mismatched data.



The university is transitioning to new platform - Microsoft Fabric – new for the whole team, adding a learning curve across the entire workflow



A large, complex pipeline introduces multiple points of failure to manage (e.g., 9 notebooks).

Data quality

- Thorough EDA surfaces inconsistencies that are expected in long-standing, multi-system institutional data. Some examples:
 - Cohort codes were sometimes missing or changed over time.
 - Credit totals occasionally decreased or stalled despite enrollment.
 - Some students had multiple academic scores or duplicate course grades, each requiring a documented resolution rule.
- Some data was not historically collected (e.g. First-Gen started in 2014) - > modeling tweaks

Activity 3

- **Imagine:**
 - You are an academic advisor. (Maybe you already are!)
 - You are about to open a dashboard covering all your advisees.
 - Your goal is to identify which ones to reach out to with an offer of extra support.
- **Consider:**
 - What do you want the dashboard to show you at a glance?
 - What might you want to be able to drill down on?

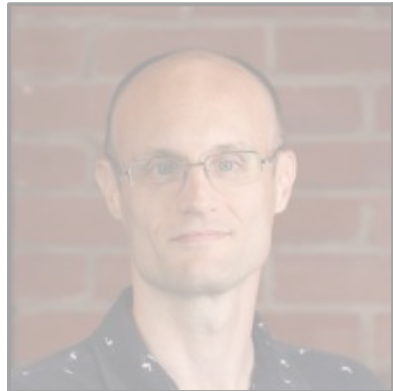
Activity 4

- **Imagine:**
 - You are the same academic advisor from Activity 3.
 - You have reached out to the advisees the dashboard flagged as most at risk.
 - Several have responded and scheduled appointments with you.
- **Consider:**
 - **What information do you want from the dashboard before you walk into those conversations with students?**

Lessons Learned

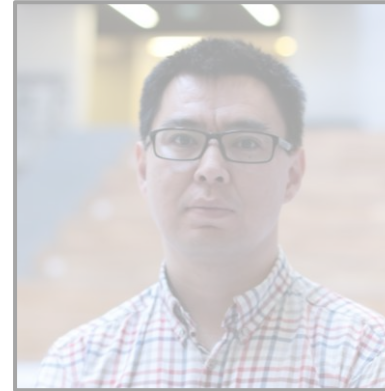
1. **Budget generously for EDA.** The uncertainty and de-obfuscation phase ran far longer than expected — plan for it up front.
2. **Partner with data professionals early and often.** Treat them as ongoing collaborators, not a one-time resource.
3. **Bad data is rarely the data team's fault.** Anomalies usually reflect institutional history, not current oversight.
4. **Documenting anomalies gives back.** Careful records of data issues are a real benefit the project returns to the data team.
5. **Check data constantly.** Validate against known truth (e.g., published grad-in-four rates) and basic reasonableness (e.g., GPA suddenly zero) to guard against pipeline failures.
6. **Data quality never "finishes."** It only gets better — proceed with good-but-imperfect data, documenting gaps for later follow-up.

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Filters

Primary Program of Study

All

Academic Standing

All

Class Standing

All

First Generation

All

ACAD Score

All

Pell Grant

All

Legal Sex

All

Ethnicity / International

All

Housing

All

Athlete

All

PG4 for Selected Students with Start Term Fall 2022 to Spring 2026

Start Term Range Begins:

Fall 2022

Start Term Range Ends:

Spring 2026

Prediction Date As Of:

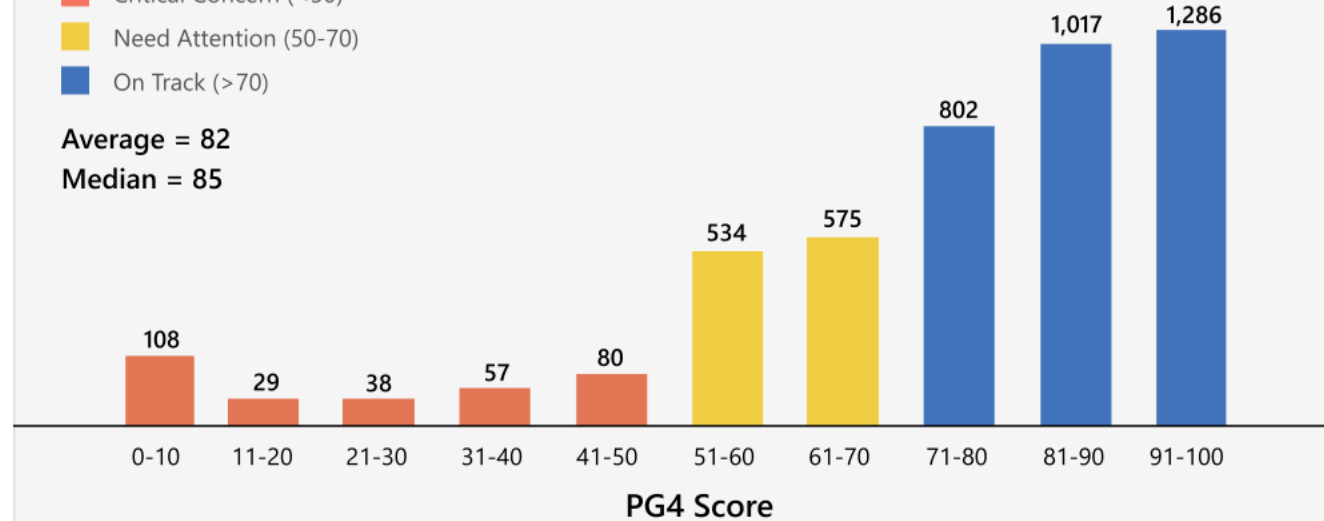
May 2026

Count ☒ Percent

Distribution of Current PG4 of Selected Students

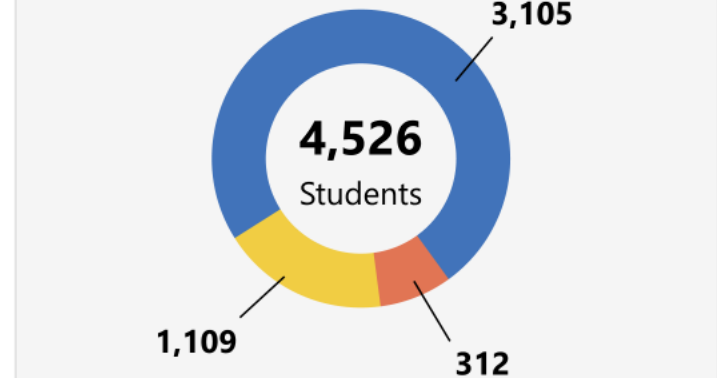
- Critical Concern (<50)
- Need Attention (50-70)
- On Track (>70)

Average = 82
Median = 85



Students in Each PG4 Category

- Critical Concern (<50)
- Need Attention (50-70)
- On Track (>70)



About the Distribution

4,526

Selected Student Count

00 - 100

Range of PG4

Fall '22 - Spring '26

Start Term Range

8

Cohorts Represented



Probability to Graduate in 4 Years

PG4 by Program of Study

Filters

Primary Program of Study

All

Academic Standing

All

Class Standing

All

First Generation

All

ACAD Score

All

Pell Grant

All

Legal Sex

All

Ethnicity / International

All

Housing

All

Athlete

All

PG4 by Program of Study

Start Term Range Begins:

Fall 2022

Start Term Range Ends:

Spring 2026

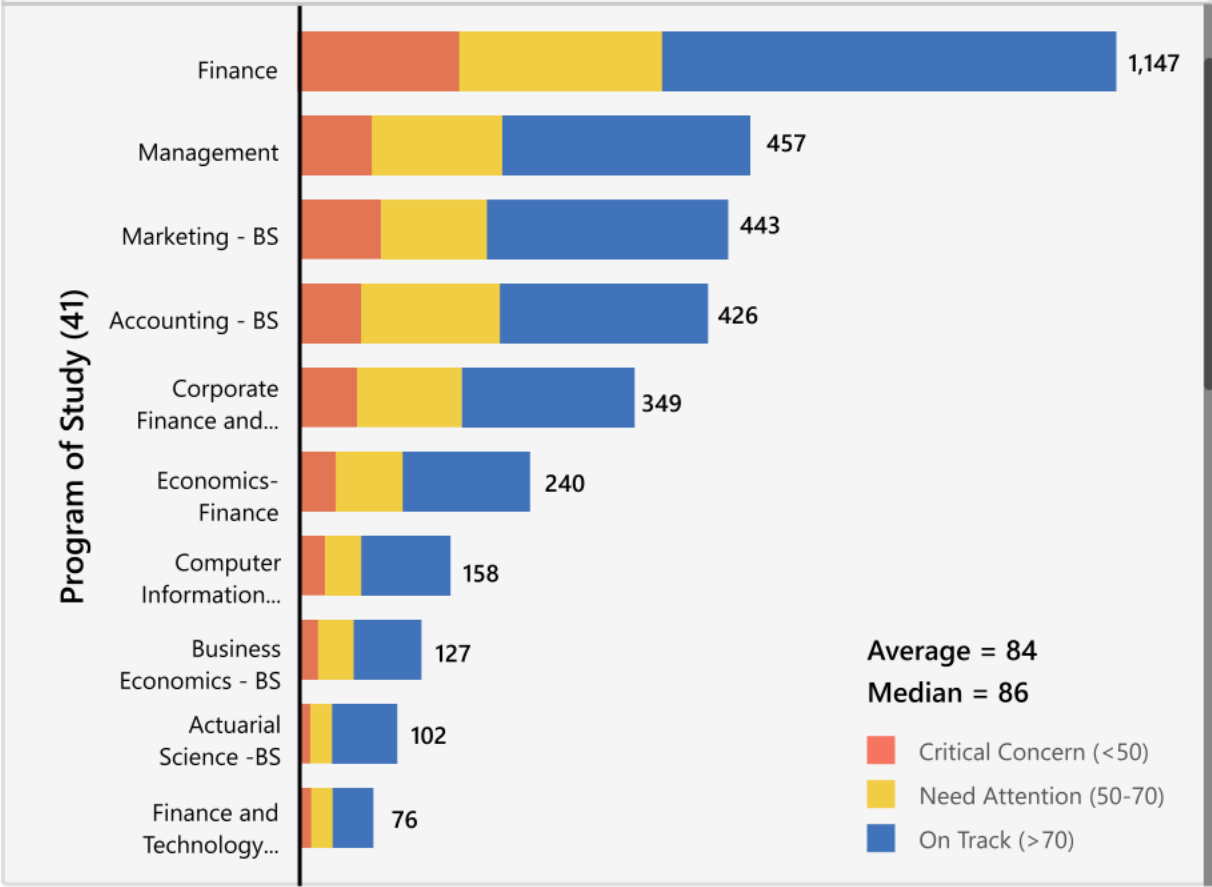
Prediction Date As Of:

May 2026

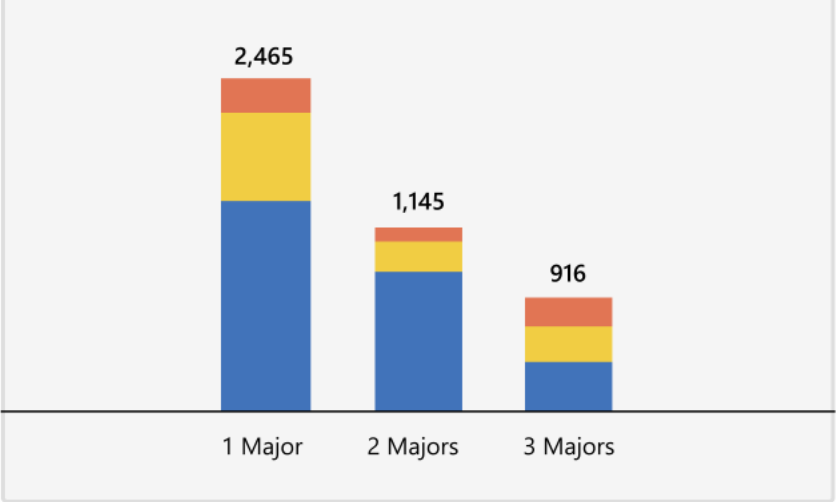
Student Program Load:

All Majors and Minors

PG4 Risk Category by Primary Program of Study



Counts of Student Program Loads



About the Distribution

4,526

Selected Student Count

00 - 100

Range of PG4

Fall '22 - Spring '26

Start Term Range

41

Programs of Study Represented



Probability to Graduate in 4 Years

Advisor Cohort Details

Select Advisor Name

Amanda Curtis

Select PG4 Range



Reset

Graphical View ☒ Roster View

Filters

Primary Program of Study

All

Academic Standing

All

Class Standing

All

First Generation

All

ACAD Score

All

Pell Grant

All

Legal Sex

All

Ethnicity / International

All

Housing

All

Athlete

All

Filtered Result

My Advisees

587

↓ 12

12.9% of all students

Total Students

4,526

100% of all students

Critical Concern

My Advisees

42

↑ 2

7.2% of all students

Total Students

314

6.9% of all students

Needs Attention

My Advisees

163

↓ 4

27.8% of all students

Total Students

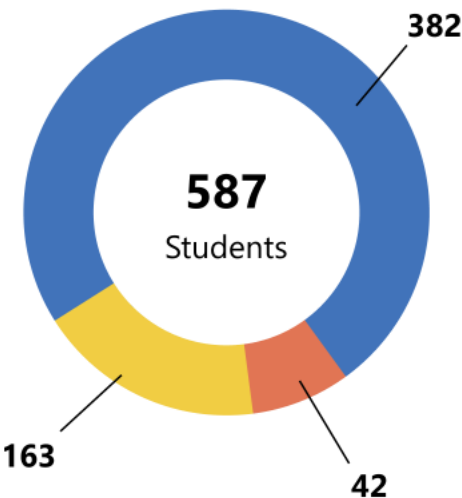
1,108

24.5% of all students

Advisor View Details

- Critical Concern (<50)
- Need Attention (50-70)
- On Track (>70)

Count ☒ Percent



Biggest PG4 Changes

Compared to December 2025

-24	McCarthy, Michael
-19	Lardis, Skye
-18	Smith, Nathan
-16	Flores, Patience
-14	Peterson, Ashley
+12	Scott, Elliot
+13	Campbell, Jacob
+16	Brooks, Sunday
+19	Mbeki, Kwame
+21	Whitestone, Emily

Students Reviewed by CAS

☒ Students with Current Good Standing Included

Sort By: Alphabetical

	1	2	3	4	5	6	7	8
Aldana, David	Good	Good	Recovery	Good	Good	Concern		
Cruz, Joaquin	Good	Good	Good	Concern	Recovery	Critical Concern	Critical Concern	Concern
Graves, Mason	Good	Concern	Good	Good	Recovery			
Green, Taylor	Good	Good	Concern	Concern				
Lopez, Yvonne	Good	Good	Recovery					
Peters, Veronica	Good	Concern	Recovery	Critical Concern	Critical Concern	Concern		
Quincy, Adam	Good	Good	Concern					
Rogers, William	Good	Good	Concern	Concern	Concern			
Tanner, Elizabeth	Good	Good	Good	Good	Concern	Concern	Critical Concern	Recovery
Wairagade, Atharv	Good	Concern	Concern	Recovery	Critical Concern	Concern		
Xu, Peter	Good	Concern	Recovery	Good	Good	Recovery		

Good Concern Recovery Separation
Recovery following separation Review



Filters

Primary Program of Study

All

Academic Standing

All

Class Standing

All

First Generation

All

ACAD Score

All

Pell Grant

All

Legal Sex

All

Ethnicity / International

All

Housing

All

Athlete

All

Student PG4 Details

Marcus A. Rivera (Marc)

Start Term: Fall 2023

Recovery after Separation

Early Expected Completion: No

Most Recent PG4 Score

31



36th percentile

Critical Concern

-34 vs. avg (65)

-7 pts since Fall 2025

-27 vs. med (58)

Top Factors Increasing PG4

Business Statistics

First Year Math

First Year CIS

Top Factors Decreasing PG4

Credits Earned

Cumulative GPA

First Year Writing

Academic Record

Cumulative GPA

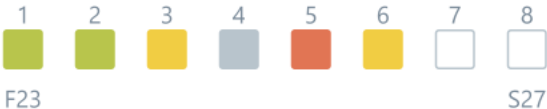
2.11

Cumulative Credits Earned

72/120

+15 since Dec 2025

Academic Standing History

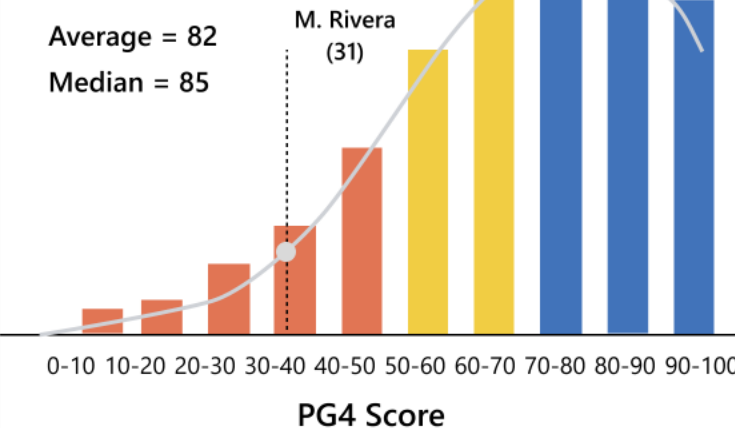


PG4 Distribution: All Students

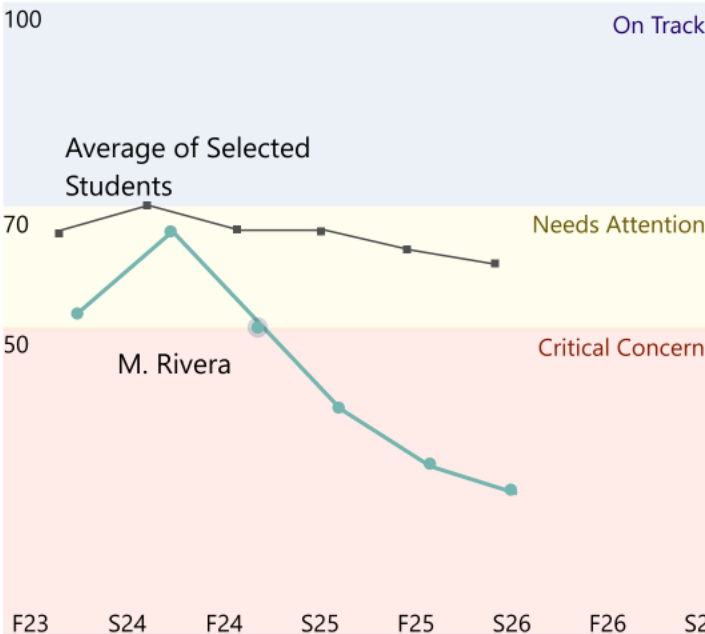
- Critical Concern (<50)
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Student PG4 by Semester with Reference Groups



Show reference group data

Average

Median

First Generation

All students

Same as student

Legal Sex

All

Same as student

Ethnicity / International

All

Same as student

Program of Study

All students

Same as student

Reset

Future work

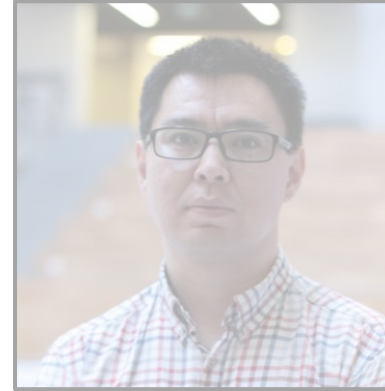
- Iterating and refining the model over time
- New types of variables we didn't have access to for this model
 - Financial
 - Academic engagement
 - Advisor interactions
- When you intervene for students' good, that makes the model's predictions get worse over time, but for a good reason.

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Probability to Graduate in 4 Years

Advisor Cohort Details

Select Advisor Name

Amanda Curtis

Select PG4 Range



Reset

Graphical View



Roster View

Filters

Primary Program of Study

All

Academic Standing

All

Class Standing

All

First Generation

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ACAD Score

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Pell Grant

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Legal Sex

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Ethnicity / International

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24.5% of all students

Advisor View Details

Search by Name or Bentley ID

Last Name ^	First Name ^	Bentley ID	PG4 ^	PG4 Change ^	Progress ^	Academic Standing ^	Start Term ^	Program of Study ^	GPA ^	Legal Sex ^
Rivera	Marcus	10016842	21	-3	Paused	Recovery	Fall 2023	Program of Study	2.43	Male
Dattachaudhuri	aminolpopihell...	10017246	24	-8	Progress	Recovery	Spring 2023	Extra Long Program of S...	2.47	Male
Ruiz Cabrera	Maria Alejandra	10017234	47	-4	Progress	Recovery	Winter 2023	Program of Study	2.34	Female
Xu	Lou	10016226	58	-13	Paused	Concern	Fall 2024	Long Program of Study	2.71	Male
Montgomery	Kelly	10016947	62	-11	Paused	Good	Fall 2025	Program of Study	2.58	Male
Banner	Marc...	10016784	64	-9	Progress	Concern	Spring 2023	Extra Long Program of S...	2.72	Female
Aldana	Josephine	10017048	68	-12	Paused	Good	Fall 2023	Program of Study	2.81	Male
Jimenez-Cort...	Pedro	Bentley ID	74	-7	Progress	Concern	Fall 2024	Extra Long Program of S...	2.84	Male
Hollingsworth	Mallory	Bentley ID	77	+5	Progress	Concern	Fall 2023	Program of Study	2.96	Female



Probability to Graduate in 4 Years

PG4 by Start Term

Filters

Primary Program of Study

All

Academic Standing

All

Class Standing

All

First Generation

All

ACAD Score

All

Pell Grant

All

Legal Sex

All

Ethnicity / International

All

Housing

All

Athlete

All

PG4 by Start Term

Start Term Range Begins:

Fall 2022

Start Term Range Ends:

Spring 2026

Prediction Date As Of:

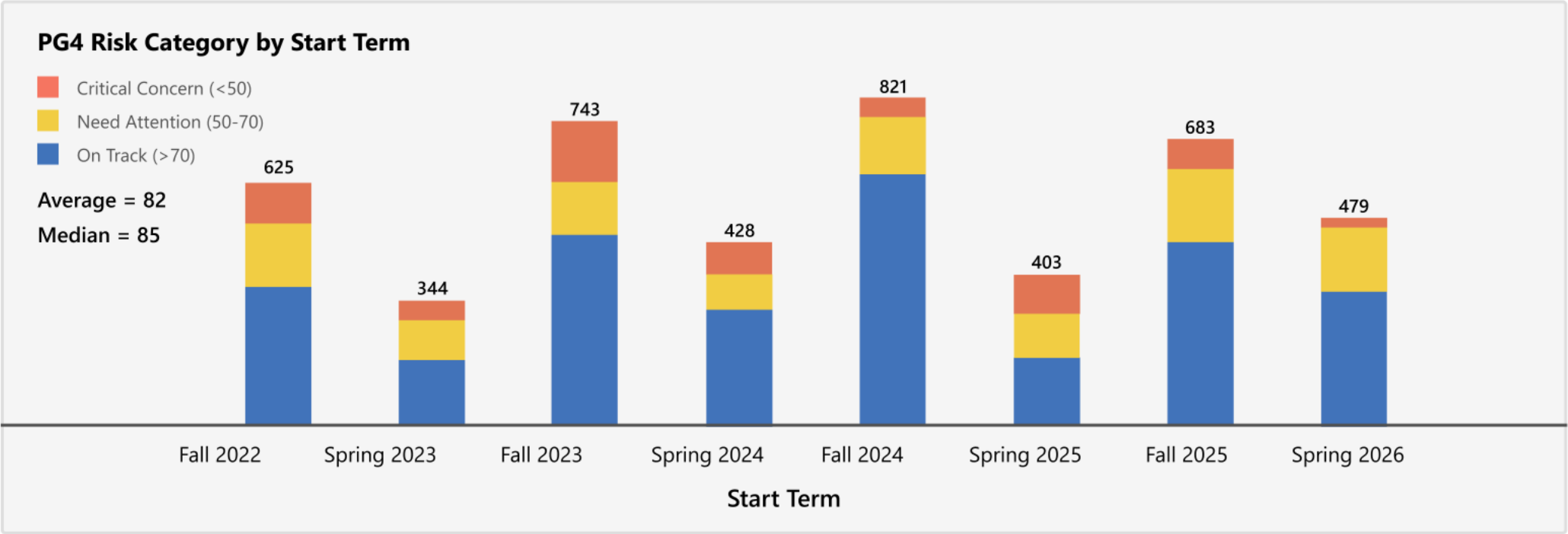
May 2026

PG4 Risk Category by Start Term

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Start Term Range

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