

From Reactive to Predictive

Building an AI-Powered Student Success Ecosystem

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Why This Matters

Consider a student balancing work, childcare, and a full course load. She keeps showing up — until one day, she doesn't. By the time anyone notices, the semester may already be slipping away.

Too often, we identify struggle after the damage is done. If we can recognize risk earlier, we can intervene sooner, support students more effectively, and create more equitable outcomes.



The Current Challenge

Student support is not only a resource problem. It is a timing problem. We often respond to visible symptoms weeks after the underlying barriers begin.

How risk usually surfaces

Missed Assignments

Often noticed in Week 6 or later, well past the point of easy intervention.

Midterm Grades

A formal checkpoint when recovery is already difficult.

Withdrawal or Stop-Out

After the student has already disengaged from the institution.

Crisis Advising Appointments

When options are already limited and the window for support has narrowed.

The Shift We Are Making

The goal is simple: move the moment of support earlier. Instead of responding after a student is already in trouble, we create systems that help us act before disconnection becomes crisis.

Reactive Support

Triggered after missed class, poor performance, or a request for help. Support is delayed, uneven, and often too late.

Predictive Support

Triggered by patterns in academic, engagement, and financial data. Advisors and faculty receive timely signals and can act with purpose.

What AI Really Means

AI is not magic, and it is not a replacement for human care. It is a practical set of tools that can help institutions identify risk earlier and respond more effectively.



Machine Learning

Learns from historical student data to identify patterns linked to risk.



Predictive Analytics

Generates risk signals that help advisors and faculty know where attention is needed most.



Automated Workflows

Supports timely nudges, outreach, referrals, and follow-up actions.

Key Indicators of Student Success

Strong prediction starts with the right data. Student risk rarely appears in a single signal; it emerges across academics, engagement, enrollment behavior, and financial stability.



Academic Performance

- First-term GPA
- Credits attempted versus completed
- Course completion patterns
- Prior academic preparation



Gateway Course Progress

- English gateway completion
- Math gateway completion
- Developmental course sequences



Engagement Signals

- LMS login frequency and activity
- Attendance patterns
- Tutoring usage
- Advising history



Financial Stability

- Financial aid status and gaps
- Outstanding balances
- Changes in enrollment load

Data & Predictive Foundations

The quality of the prediction depends on the quality of the data, the soundness of the model, and the institution's ability to connect insight to action.

1. Audit Data Sources

Review SIS, LMS, tutoring, advising, and financial aid data to understand what is available and what is missing.

2. Define Predictive Indicators

Identify the variables most associated with risk for your students and your context.

3. Build and Validate Models

Use historical data to test models and examine both accuracy and equity across student groups.

4. Connect Predictions to Action

Turn model output into clear, usable alerts that fit advisor and faculty workflows.

Advisor Dashboard

A good dashboard does not just display data. It helps staff decide who needs attention, why they were flagged, and what action should happen next.

Risk Scores

Show the likelihood of withdrawal or academic difficulty.

Key Indicators

Highlight the signals driving the alert, such as attendance, LMS activity, grades, or financial stress.

Caseload Priorities

Help advisors focus on the highest-need students first.

Intervention Tracking

Record outreach, referrals, follow-up, and outcomes over time.

Implementation Roadmap

Building a predictive student success ecosystem is not a single technology decision. It is a phased institutional strategy.

01

Phase 1 — Audit Data and Define Indicators

Identify available data sources and the strongest early warning signals.

03

Phase 3 — Connect Predictions to Action

Translate model output into alerts, workflows, and staff-facing tools.

05

Phase 5 — Evaluate and Improve

Measure impact on retention, progression, and equity gaps, then refine the system over time.

02

Phase 2 — Build Predictive Models

Use historical academic, enrollment, and engagement data to generate risk scores.

04

Phase 4 — Deploy AI Agents and Automation

Use automated nudges, reminders, and referrals to support timely intervention.

Responsible AI & Human Oversight

“AI should support human decision-making, not replace it. In student success work, trust, transparency, and accountability must remain central.”

Transparency

Staff should understand why a student is flagged.

Bias Monitoring

Models should be reviewed regularly to avoid reinforcing existing disparities.

Student Data Rights

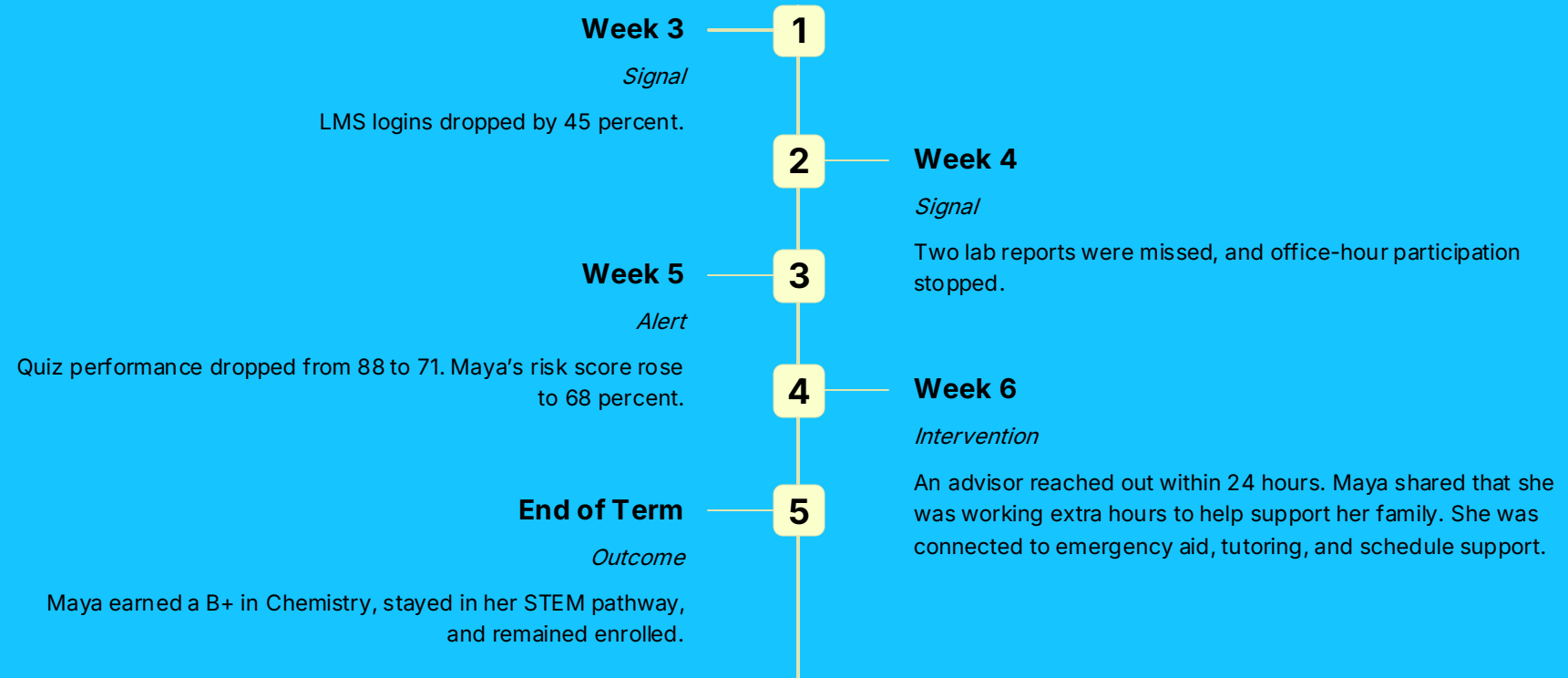
Students should know how their data is being used and have a voice in that process.

Ethical Use

Data should be used to support opportunity, not restrict it.

Use Case: Maya — First-Time, Full-Time STEM Student

Maya's early engagement changes signaled risk before she failed the course. Because the institution responded early, the outcome changed.



Use Case: James — Returning Adult Learner

James illustrates how predictive support can help adult learners manage competing responsibilities before they disengage.

Week 2 · *Signal*

James was flagged as medium risk based on a financial aid gap and part-time enrollment status.

1

2

Week 4 · *Alert*

An automated nudge prompted outreach and surfaced his need for flexible scheduling and financial support.

3

Week 6 · *Intervention*

An advisor connected James to emergency aid and helped adjust his course load.

4

End of Term · *Outcome*

James completed the semester and re-enrolled for the next term.

Institutional Transformation

When AI is implemented thoughtfully, the institution changes with it. The shift is not only technical; it is cultural, operational, and strategic.

Before

- Late alerts after students are already in trouble.
- Manual caseload review and inconsistent follow-up.
- Siloed systems and disconnected data.
- Students falling through gaps.

After

- Earlier signals that support timely action.
- Prioritized outreach and more coordinated intervention.
- Shared insight across advising, academics, and support services.
- More proactive and equitable support.

Pilot Targets and Early Success Metrics

We are not waiting for perfect data to act. These are the measurable outcomes we are tracking as we build and refine our predictive ecosystem.

2–3 Weeks Earlier

Earlier Outreach

Identify at-risk students earlier in the term, before disengagement becomes withdrawal.

15–20% Reduction

Stop-Out Risk

Decrease the rate of mid-semester stop-outs among flagged students who receive timely intervention.

10+ Point Gain

Course Completion Rate

Improve gateway course completion rates for students connected to targeted support.

Narrowing Gap

Equity Outcomes

Reduce disparities in retention and completion rates across race, income, and first-generation status.

Targets are based on pilot design benchmarks and comparable institutional outcomes. Results will be measured and reported at end of pilot term.

What We Are Building

Our Vision

A system that sees students before they disappear.

Workflows that enable advisors and faculty to act earlier, faster, and with greater precision.

An institution that advances equity, not only retention.

The Call to Action

01

Start with your data.

02

Define the indicators that matter most.

03

Pilot, learn, and scale with purpose.

The technology is here. Our students cannot afford for us to remain reactive.