

## Moving the Needle on Predictive Analytics

*In using data to improve student success, higher education is at a transition point, pivoting from harvesting data to learning how to use it strategically in developing interventions—and getting those findings to faculty and students so they can have an impact.*

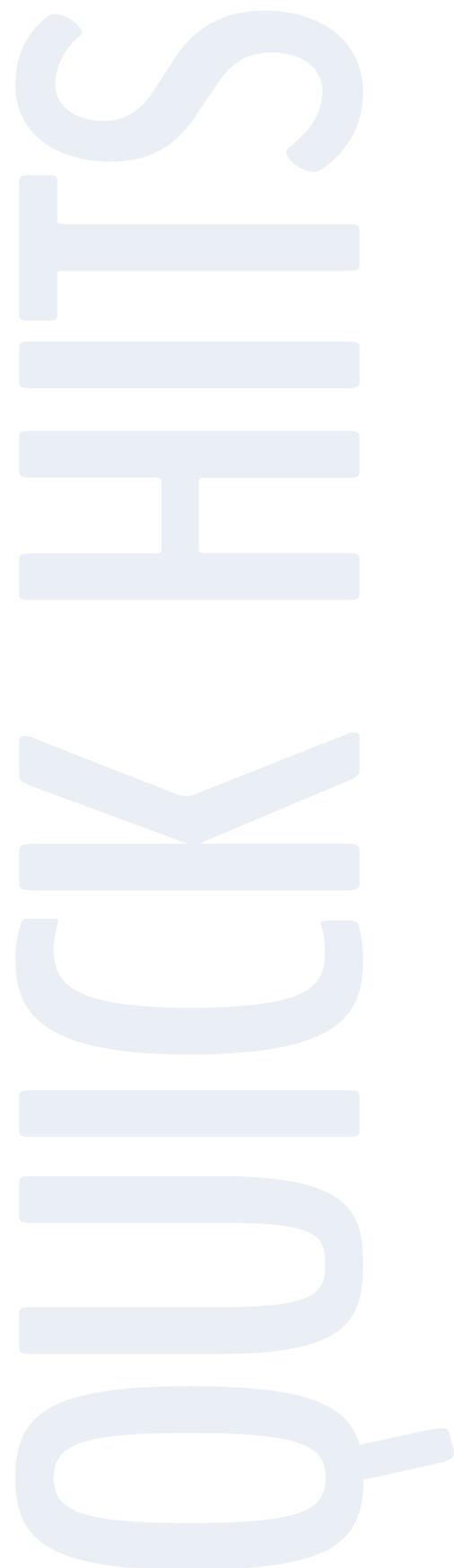
When it comes to data on campus, the challenge increasingly seems to be that we’re drowning in information, but thirsting for wisdom. That seems especially true regarding the use of data for improving learning, retention, and completion. Technology makes it possible for colleges and universities to be increasingly more sophisticated in their capacity to collect, store, and mine data pertaining to student learning. At the same time, though, our skills in making meaning of those data—and using them to design interventions to improve student success—have yet to reach a commensurate level of refinement.

As Ellen D. Wagner, chief research and strategy officer for the Predictive Analytics Reporting (PAR) Framework, has observed, the central challenge, distilled to its essence, is to gather data, turn the data into information, and use that information to help learners. Fulfilling those three basic steps may be easier said than done, but some pioneers are developing innovative pathways to help universities use data strategically.

### **CLARIFYING TERMINOLOGY**

Among many terms that apply to the use of data in higher education, “predictive analytics” encompasses the use of modeling to pinpoint variables that can help predict the aspects of the student experience that contribute to academic success. The value of predictive analytics is in building on an analysis of those variables to design interventions that improve student progress. While colleges and universities are getting better at collecting data, only a relative handful are making full use of those data by using predictive modeling to design improvements.

In a recent presentation, Joel L. Hartman, vice provost for information technologies and resources at the University of Central Florida, offered a helpful distinction between predictive analytics and its perhaps less-sophisticated cousin, descriptive analytics. Whereas the latter might seek to determine the number of student logins and page views in a course’s learning-management system, Hartman suggested, the former seeks answers to deeper questions, such as which students show behaviors that put them at risk for not completing the course. Similarly, descriptive analytics might seek to find out which course tools students are using, while predictive analytics would take a deeper look at understanding the tools and course content that correlate to student success, with the goal of informing meaningful interventions.



Mark David Milliron, a former chancellor of Western Governors University Texas and a former deputy director at the Bill & Melinda Gates Foundation, is the co-founder and chief learning officer of Civitas Learning, Inc., which works to accelerate adoption of predictive analytics, makes another useful distinction. Right now, he says, many data initiatives in higher education are “what I would call accountability analytics,” focused on meeting the needs for information of administrators, accreditors, and trustees. Those kinds of analytics are vital, of course, particularly given the current clamor from lawmakers and the public for higher education to be more accountable, efficient, effective, and transparent in their business practices. But Milliron contends that higher education needs to go further.

Arguing that higher education needs to figure out how to use data more intelligently, Milliron urges universities to put as much energy as they put into accountability analytics into what he calls “action analytics,” which he frames as “bringing data to faculty, advisors, and students, people who are on the front lines of learning” so that the data can help students “navigate learning journeys.” In that work, Milliron says, universities need to actively become “student success scientists.”

In a similar vein, Wagner has called on colleges and universities to learn better ways of seeing patterns in the data PAR collects to find what she calls “actionable information.” Predictive techniques draw on that actionable information to help educators create interventions and get them in the hands of faculty and students in ways that will improve student learning and success.

With anonymized data from some 2 million students, the PAR network “can literally look at every single one of those students and find the factors that are likely to affect them,” Wagner says. She is quick to note, though, that simply knowing who is at risk and why is not enough. “What none of us have expected with predictive analytics is that simply coming up with the predictive models wasn’t going to be enough,” she says. “If you don’t have an action strategy that goes with the predictions, knowing who is at risk is almost a liability.”

The “promise of the predictive,” Wagner says, “is the recognition that if you can connect predictive to the types of interventions that make the most sense for the students who are predicted to be at risk, that you’ve actually been able to find a true way to make the analytics matter more.”

### COMPLICATED CONVERSATION

Some administrators and faculty continue to resist this kind of approach. “Many educators are still not convinced that we can quantify all of the true value constructs around the somewhat intangible things that we in education do,” Wagner says. Consequently, she notes, data mining and “the predictive transactional type of ways of thinking” can be controversial and anxiety-inducing among educators. Adding to these tensions is the reality that in this age of accountability there is pressure on administrators to get analytics right even when there is no one obvious path to that goal. That can lead to the proverbial analysis paralysis. Another complication is that



faculty may be suspicious in part because, as Wagner observes, “we promise analytics as the carrot for improvement, and in most implementations we revert to using them as sticks.”

These tensions are exacerbated, Wagner suggests, by the dilemma that “what’s going on right now in using analytics really creatively is a push into territory where we’ve never really been before.”

## EMERGING SOLUTIONS

Nonetheless, there is a strong sense among pioneers in this space—and on the part of some prominent funders—that pushing into this new territory will pay significant dividends in improved student success. To that end, those pioneers are developing innovative new solutions, as these examples suggest:

- The [Predictive Analytics Reporting \(PAR\) Network](#) has published common data definitions using Creative Commons to help identify specific risks and opportunities for student success. Evidence about what works in learning that is derived from comparing data from many students and courses provides a more holistic perspective and deeper insights than data from one institution alone. PAR members can use data from the network to benchmark their own practices for supporting student progress and to design actionable strategies for mitigating student risk for not meeting academic goals.
- [Degree Compass](#), a course recommendation system developed at Austin Peay State University and acquired last year by [D2L](#) (formerly Desire2Learn), uses predictive analytics technology based on grade and enrollment data to help students complete their degrees. For example, the model combines hundreds of thousands of past students’ grades with a student’s transcript to make individualized recommendations about how well a given course might help a student progress through his or her program.
- [Civitas Learning](#) developed predictive models that leverage historical student data at University of Maryland University College. A Student Success Application delivers the predictions in actionable ways to administrators and advisors, who can then use the information to understand which students are at risk, and apply relevant interventions and support. A student’s risk predictions update continually throughout a course, providing increasingly accurate measures of the likelihood of course completion.
- More than 100 institutions use the [Education Advisory Board’s Student Success Collaborative](#), a predictive model helps colleges and universities identify at-risk students and uncover systemic obstacles to degree completion.
- The open source [Student Success Plan](#), developed at Sinclair Community College (OH) and designed to improve retention, academic performance, persistence, graduation rates, and time to degree, supports a holistic coach-

ing and counseling model that expedites proactive interventions for students in need.

## WHERE DO WE GO FROM HERE?

Experts suggest that we are really just in the beginning phases of maximizing the power of predictive analytics. So where do we go from here? Candace Thille, a senior research fellow for the Office of the Vice Provost for Online Learning and assistant professor in the Graduate School of Education at Stanford University (CA), is the founding director of the Open Learning Initiative. She says that one challenge is “collecting the data at a fine enough grain size so that we can get insight into the student learning trajectory.”

“For learning analytics to understand more about the student learning process, and to be able to design interventions that improve student learning,” Thille also suggests that assessment and intervention development processes need to engage more than single faculty members working alone to test what works. Rather, she says, faculty need to collaborate with cognitive and social psychologists, software engineers, learning design specialists, and other experts to collaborate in designing activities that will help students achieve desired outcomes. “The power really comes from the interdisciplinary teams,” she says.

Thille says the process should start by defining desired learning outcomes “in very clear, observable, and student-centered ways.” Taking full advantage of available technology, what we know about human learning, what is important knowledge in given disciplines, and other critical criteria, such teams can “build an underlying model that maps the interaction of the learner to skills and concepts which then map to the outcomes,” she says. “Once you have thousands of learners using the environment, then you can compare the data to the fit of your model, and refine your model, validating it against the data. In that way, you can start to build analytics systems that improve student learning.”

Moving the needle on predictive analytics will require some fundamental shifts in behavior, Thille suggests. First, she says course design needs to shift from an intuitive approach—“this is how I’ve always done it and what I’ve always asked my students”—to one that is more evidence-based. She also says that more research about learning needs to be channeled directly into teaching practice. Thille envisions a cycle of continuous improvement where theory-based interventions can be tested in practical learning environments, yielding data that inform ongoing refinements. “We need the bottom-up, looking-for-the-patterns-in-the-data approach,” she says, “but we also need a top-down approach that starts with our current theories” and enables ongoing refinements and testing of interventions and hypotheses.

Both Milliron and Wagner suggest that critical next-generation solutions are likely to come in the form of apps, tools that are not as ponderous as full systems but which can capture specific data from instruction and learning and—importantly—produce relevant data that can feed directly to faculty and students in forms that can change

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behaviors to improve success. Noting that “we are already showing dramatic lift” in student performance with such apps, Milliron envisions an ecosystem of apps that act in concert.

Milliron says a critical challenge is determining how to use data to “figure out what is actually creating lift.” But he is quick to add a relevant caution. “The data are a predicate, not a solution,” he says. “Predictive models are great, but you need to first be able to understand what your problem is.”

Currently, Milliron believes, “a lot of the analytics are being used in simplistic ways and basically only to help at risk students.” Moving the needle for predictive analytics hinges in part, he says, on applying them to help all students. “At the most advanced levels, I think what we’re going to see is people concerned as much about raising the ceiling as they are about raising the floor,” he says.

“I jokingly say that we are in the world of aspirin and aspiration,” Milliron says. “There’s a lot of pain out there because people are being pushed by student success initiatives that want to see greater completion. And then you have people who are on the aspiration side. They really care about deeper learning. They want students to learn in a more sophisticated way. And they want to connect to the workforce so that students are prepared for the jobs they are going into. The great thing is that [predictive analytics] can actually help an institution deal with both of those issues.”

## RESOURCES

Civitas Learning, Inc. 2014. “Predictive Analytics: Reading Resources.” *Civitas Learning Space*. [http://www.civitaslearningspace.com/predictive\\_analytics\\_reading\\_resources](http://www.civitaslearningspace.com/predictive_analytics_reading_resources).