A Toolkit for Building Organizational Capacity for Analytics

Leadership & Investment

Processes & Practices

Skills & Values

Technology & Infrastructure

Culture & Behaviors

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This section is an excerpt from *A Toolkit for Building Organizational Capacity for Analytics*.

**Stages in the Analytics Process**

The ECAR Report stipulated a five-stage process for analytics that is portrayed in Figure 4e:

- Start with a strategic question,
- Find/Collect the appropriate data to answer that question,
- Analyze that data with an eye toward prediction and insight,
- Formulate and present in ways that are understandable and actionable, and
- Feedback into the process of addressing strategic questions and identifying new ones.

![Figure 4e. The analytics process](image-url)
### 2.4 Actions for Optimizing Student Success Using Analytics

Optimizing student success encompasses all the actions, activities, policies, and practices that actively support student success at all stages of the student experience. In collecting information from our selection of leading practitioner universities, we used the Davenport/Harris framework as one point of reference. We embedded the elements of this framework in the interview questions about their institutional organizational capacity to deal with data, information, reporting, query, and analytics.

The Davenport/Harris framework can be used to describe current analytics capabilities, future aspirations, and the gap between them.

![Table of Davenport/Harris Framework](image)

**Figure 5. The Davenport/Harris framework**
The Davenport/Harris framework cites “Optimization – achieving the best that can happen” as the highest pinnacle of achievement of data/information/analytics use. Davenport/Harris focused on how businesses and industries used analytics to optimize competitiveness. Analytics can be used to enhance and optimize student success only if serious focus and strategic infrastructure development occurs. In higher education, analytics optimizing student success consists of an array of actions that institutions pilot test, then embed in their academic and administrative support processes.

We found that the success of learners in achieving their objectives was enhanced by a wide range of complementary initiatives and actions. These include both established practices and many emerging developments with comparable promise. Institutions today are discovering ways to proactively optimize student success by deploying combinations of actions and interventions to achieve the best outcomes possible.

**Norris/Baer Framework: Optimizing Student Success through Analytics**

These initiatives and actions are supported by increasingly sophisticated combinations of the reporting, query, and analytics included in the Davenport/Harris framework, and more. To describe the analytics activities of our leading institutions, we use the following array of analytics-enabled student success activities. This array emerged from analysis of the actual practices of leading institutions.

Figure 6 describes the seven elements of the framework and provides examples. This framework maps the actual initiatives institutions are undertaking today. It also suggests migration paths to future practice. In theory, adding improved versions of these seven categories of actions can continue to improve retention and the rates of achieving academic goals (competencies, certificates, degrees, employment). The categories are important as a suite of activities, and institutions gain more improvements over time when integrating support in each of these areas.

**Manage the student pipeline.** As part of their strategic enrollment management (SEM) initiatives, institutions have been using longitudinal analytics and predictive modeling to attract and select students likely to achieve success. They have also shaped policies, practices, and processes to identify and provide a variety of support services to at-risk students, enhancing their chances of educational success once enrolled. These practices have been extended into institutional programs for the first-year experience, gateway courses, and retention improvement.

Among our 40 institutions, virtually all are using analytics to manage and improve the pipeline of incoming students. Prospective additions to their SEM practices could include attracting and selecting high-performing students who motivate and support other students, helping to enhance their peers’ success and the institution’s reputation.
## Norris/Baer Framework: Optimizing Student Success through Analytics

<table>
<thead>
<tr>
<th>Elements</th>
<th>Description</th>
<th>Examples</th>
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| 1. Manage the student pipeline                | Scientifically refine strategic enrolment management of the student pipeline | • Use data mining and predictive analytics to improve the recruitment, admission, and enrolment of entering students (raise numbers and improve chances of student success; and  
  • Use longitudinal and predictive analytics to craft policies for improving success of at-risk students. |
| 2. Eliminate impediments to retention and student success | Eliminate structural, policy, and programmatic impediments to retention and success. | • Use analytics to support comprehensive first-year programs;  
  • Eliminate bottlenecks in courses and program progressions; unreasonable pre-requisites and other requirements; and  
  • Use predictive analytics to shape policies and practices to enhance retention in sophomore-senior years. |
| 3. Utilize dynamic, predictive analytics to respond to at-risk behavior | Embed analytics in academic and administrative support processes to enable real-time interventions dealing with at-risk behaviors, both academic and co-curricular. | • Use dynamic, predictive analytics to determine at-risk behavior in courses early in the semester; Embed predictive analytics in processes; and  
  • Monitor levels of student engagement in academic and co-curricular activities and intervene with students who can be saved. |
| 4. Evolve learner relationship management systems | Build tracking systems that can track and manage the many facets of learner progress and identify and respond to at-risk behavior. | • Create the learner equivalents of customer relationship management functionality, supported by predictive analytics; and  
  • Extend dynamic, predictive analytics to learner relationship management. |
| 5. Create personalized learning environments/learning analytics | Embed personalized learning analytics into learning management systems and learner relationship management systems. | • Create personalized learning modes with embedded predictive performance analytics;  
  • Use these analytics-rich systems to personalize learning outcomes; and  
  • Create learning experiences reaching beyond formal curricula. |
| 6. Engage in large-scale data mining           | Use data mining to illuminate pathways to student success and discover unforeseen insights. | • Leverage data mining to drive predictive modelling in processes;  
  • Use forensic data mining to explore unthought-of correlates of success; and  
  • Engage in cross-institutional comparisons and cross-sectoral comparisons. |
| 7. Extend student success to include learning, workforce, and life success | Expand the definition of student success to include the entire student lifecycle – cradle to career, including learning, work, learning-to-work transitions, and workforce success. | • Extend into Alumni analytics;  
  • Undertake data mining spanning institutions, industries, and sectors; and  
  • Pioneer pathway-to-success analysis. |

Figure 6. Norris/Baer framework
Examples of managing the student pipeline include:

- Virginia Community Colleges is actively engaged on high school campuses to advise, recruit, and prepare students for successful college entrance.
- University of Michigan utilizes SEM to identify at-risk students and provide mentoring and support services that have dramatically improved the success of these students.

Eliminate impediments to retention and student success. Many institutions have unwittingly erected structural, policy, and programmatic impediments to student progress, retention, and success. Many institutions and groups, like the Education Trust, have demonstrated the effectiveness of assessing and eliminating academic bottlenecks, enhancing gateway courses, focusing on the first-year experience, and undertaking other measures shown to improve student success for all students, but especially at-risk students.

These approaches are widely practiced and have produced measureable success. The most effective of these programs use predictive analytics to identify and support at-risk students.

Examples of such actions include:

- Offering comprehensive “first-year experience” programs that focus on the first year, when attrition is more pernicious. This allows students to learn early what constitutes successful learning behavior.

- Undertaking structural realignment to eliminate bottlenecks in course and program progressions, unreasonable prerequisites, and other requirements having unintended, detrimental consequences. The report Winning by Degrees relates that in order to improve productivity, campuses must focus on reducing nonproductive credits; that is, reducing failed credits and withdrawals, focusing on reducing credits, and honing in on more core instructional offerings. Designing curriculum around a full summer semester increased the timely completion for students at BYU–Idaho and University of Northern Texas.

- Using predictive analytics to shape policies and practices to enhance retention in sophomore through senior years. These practices include limiting the number of credits lost during transfer and strict policies on withdrawal and academic progress. Strengthening and enforcing transfer policies is especially important in guarding against redundant credits. In addition, focusing on “killer courses” and monitoring the amount of Ds, Fs, and Withdrawals in courses is important in understanding where students are getting hung up and where progress is stalled.

All of the 40 institutional leaders are using analytics to remove barriers to success. Prospective enhancements include cross-institution analytics, to identify transferrable ways to spot and remove impediments to success.
Use dynamic predictive analytics to respond to at-risk behaviors. The first two categories deal with mitigating the risks for at-risk students and eliminating risk-enhancing aspects of policies, processes, and structures. This third category involves using analytics to dynamically identify and deal with at-risk behavior for all students, preferably in real time or as close to real time as possible. It features embedding analytics in academic and administrative support processes to enable real-time interventions, in some cases automatically.

A cluster of leading-edge institutions are using the new generation of analytic applications to enable dynamic analysis of student performance, inform students, and provoke interventions immediately when students display at-risk behaviors. Dynamic viewing means that the end user can literally “push a button” or view an institutional dashboard or Bloomberg-type displays to see updated versions of standard reports on student progress and status. Or users can access a user-friendly data utility to easily select different combinations of variables, and then easily request new reports and queries that can lead to dynamic drilldowns that identify individuals among groups of students displaying risky behavior. Alerts and tailored interventions follow.

Many of these practices can scan course, student, and financial information. They can even scan not just academic behaviors but also the intensity of the student’s engagement in co-curricular activities and administrative systems. Many use predictive analytics so that at-risk behavior thresholds can be established as tripwires that provoke automatic, yet tailored, interventions, depending on the students’ characteristics.

The best of the leading institutions are progressively embedding predictive analytics into both academic and administrative processes. In this way, they can automatically provoke responses to at-risk behavior and track/manage learner outcomes. Among the for-profit institutions and online institutions in our group, embedded predictive analytics are standard operating procedure.

- Purdue’s Signals program, which has been productized by SunGard, is the best-known example of embedded, predictive course analytics. It produces red, yellow, and green evaluations of student behaviors in comparison with past behavior of successful students.

- Rio Salado College has developed an eighth day “at risk” model that assesses the likelihood of a student’s successful completion using past enrollment, LMS activity data, and current enrollment status as indicators. They also have developed the SOS – Status of Student – model, which implements warning levels on a weekly basis using frequency of student login, site engagement, and pace in completing a course as indicators.

- The University of Phoenix has studied which factors are “good” predictors and “low” predictors for course completion. They have found that good predictors include scores earned in current course, credits earned, credits attempted, difference between past and current scores, prior course points, GPA, and financial status.
• Arizona State University has improved its retention rates by 4–5% through leveraging Sun Devil Tracking and eAdvisor.

• American Public University System (APUS) has created a predictive model that is 91% accurate in predicting student disenrollment for the coming five semesters. They take a comprehensive look every week at all enrolled students, ranked in order based on their likelihood of not being retained.

• Other variations on embedded, dynamic, and predictive analytics are on display at many of the other institutions: UMBC and Coppin State University, to name a few. More details will be provided in subsequent versions of this report.

Evolve and leverage learner relationship management systems. Student information systems are transaction-based systems that are a module in institutional ERP systems. Learning management systems are organized around courses. Advising and customer relationship management systems are organized around individuals. One of the key developments in analytics systems is the evolution of a variety of analytics-infused systems that are essentially “learner relationship management” approaches. Most combine embedded analytics to flag at-risk behavior.

Customer relationship management builds on what experts in service science and service systems are applying to higher education.

Service science asserts that the customer and the service provider co-create value. Value is not in the product (e.g., a course or a degree) but in the experience created by interaction, such as that between faculty and students. For example, the real value of a course may lie in the critical thinking a faculty member encourages in a student, the integration of content with real-world experience, and the motivation to continue learning and solve important problems.

Leading institutions and vendors are developing the first generation of LRM tools/applications that embed CRM capabilities. For example:

• Northeastern University has adapted Salesforce.com to create a sort of LRM system for advancing student success.

• Sinclair Community College has developed the Student Success Plan (SSP), a case management and intervention software system it is turning into an open-source product with a community of practice of users at institutions deploying this holistic advising utility.

• South Orange County Community College System has developed SHERPA, a system for following student progress and providing “nudges” toward success.
• Arizona State University’s eAdvisor System enables predictive analytics-enabled evaluation of student behavior and learner tracking against norms.

• Capella University’s learning-objective mapping system provides guidance for each student and is at the heart of their competence-based approach to learning and student success.

• Rio Salado’s Student Success Model monitors each student’s progress/success/at-risk indicators.

• Retention systems and services such as those offered by Starfish and EBI/MAP-Works use many LRM-like features.

• ERP-for-online-learning systems like TopSchool can provide an LRM look for dealing with students.

• New systems under development by vendors enable the dynamic evaluation of learner success relative to predictive analytics-based norms in all courses, providing a more holistic view than course-by-course assessments.

These early-stage systems can be positioned to evolve and accommodate personalized learning practices and learner analytics at the course/learning experience level. Future versions of this report will describe in more detail the development of LRM capabilities.

Create personalized learning environments/learning analytics. Personalized learning practices and learning analytics are being actively embedded into academic courses and programs so that learning experiences can be fashioned to optimize learning outcomes for each individual. Over the next few years, learning analytics practices are positioned to grow considerably in sophistication, with widespread application and deployment. An area where personalized learning environments are being explored is through the Bill & Melinda Gates Foundation project in the Next Generation Learning Challenges initiative. This initiative actively supports prototype projects that are piloting personalized learning, open educational resources, and learning analytics concepts.

Another Bill and Melinda Gates Foundation initiative is the IPAS, Individual Planning and Advising Systems. Nineteen campuses and vendor solution partners are scaling outstanding student success tools to improve student learning and success. These tools will empower students, faculty, and advisors to improve the mapping of successful student choices, behaviors and interventions tailored to improve student success. They will also encourage the development of a robust solution provider community, whose offerings are continuously adapting in response to institutional needs.

Over time, personalized learning and learning analytics will add another dimension to the improvement of learner success and completion of degree goals. These innovations will require both existing enterprise systems and next-generation learning management systems to accommodate new course structures, fresh approaches to evaluation and grading, and other
innovative practices. They likely will hasten and shape the next generation of core systems in the cloud. They will also foster the development of open, free-range learning alternatives that will operate parallel to and outside existing institutional learning and enterprise systems.

The dual potentials of personalized learning and learning analytics are nicely portrayed by George Siemens and Phil Long in a recent *EDUCAUSE Review* article. At the same time, personalized learning environments and enhanced learning analytics will stimulate the emergence of immersive learning experiences that occur outside of institutional learning environments and the enterprise systems that support them. One of the important challenges that will confront enterprise systems for student success is how they will accommodate, incorporate, emulate, and certify aspects of free-range, do-it-yourself personal learning more attuned to real-world experiences, employers, and emerging challenges. These learning and competence-building opportunities will operate beyond the restrictions of the academic curriculum.

**Engage in large-scale data mining.** As Vernon Smith noted in *Game Changers,*

Colleges and universities collect mountains of data in their student information, learning management, and other systems. At the same time, students come and go – often at predictable “loss points” such as the transition from high school to college, during remedial education, and so on.

In one scenario, higher education would use the power of information technology to mine student information and data on a massive scale across multiple institutions. This would involve aggregating, mining, and identifying the key momentum and loss variables, and then scaling up solutions that effectively address those factors. The idea would be to then create predictive models through the use of advanced statistical modeling that would identify possible stumbling blocks and help drive early interventions for students, especially low-income young adults and minorities. A growing body of best practices and interventions that remove barriers to student progress and success exists, but those interventions would be better informed if they were based on what the research and actual behaviors indicate, rather than on anecdotal notions or experience alone. (Vernon Smith in Oblinger, 2012)

Data mining is the process of discovering new patterns from large data sets involving methods at the intersection of artificial intelligence, machine learning, statistics, and database systems. Most of our 40 institutions are engaged in some form of large-scale, longitudinal data analysis and comparative research to discover insights into “what works” in making students successful. The best of such efforts don’t just answer preset research questions; they mine the data to identify unexpected patterns and relations and thereby frame and answer fresh questions.
Most of the institutions interviewed expect to engage in larger-scale data-mining projects in the future. These will be used forensically to explore unthought-of correlates of student success and linked to reinventions and retuning of policies, process, and practices.

In addition, cross-institutional data mining for insights is growing. For example the Predictive Analytics Reporting (PAR) Project being undertaken by the Western Interstate Commission for Higher Education (WICHE) has created a federated data set for six institutions and almost 800,000 student records; this will enable data mining across the data set. The project is deconstructing the problems of retention, progress, and completion to find solutions to decrease loss and increase momentum and success. The PAR partner institutions are federating and aggregating more than 600,000. Now with sixteen WCET member institutions, over 1,700,000 anonymized student records and 8,100,000 institutionally de-identified course level records, the PAR Framework offers educational stakeholders a unique multi-institutional lens for examining dimensions of student success from both unified and contextual perspectives. They do this by de-identified online student records and are applying descriptive, inferential, and predictive analytical tests to the single pool of records to look for variables that seem to affect student achievement. Partners include the following with founding partner institutions designated with *.

- American Public University System*
- Ashford University
- Broward College
- Capella University
- Colorado Community College System*
- Lone Star College System
- Penn State World Campus
- Rio Salado College*
- Sinclair Community College
- Troy University
- University of Central Florida
- University of Hawaii System*
- University of Illinois Springfield*
- University of Maryland University College
- University of Phoenix*
- Western Governors University

Pearson/eCollege is using its cloud-based operations to enable data mining to identify student success factors and patterns across its institutional clients. Moreover, consortia of institutions are
pursuing cross-institution comparisons of “what works” and analyzing the complexity of student transitions among different institutions. Many states have K–16 initiatives that are using large data sets to explore issues relating to high school-to-college transitions.

The University of Central Florida leverages its PhD-level data-mining program, which harnesses faculty and students to engage and solve institution-wide grand-challenge problems such as fundraising and retention. They have successfully used advanced data mining to successfully identify through predictive analytics 80–85% of at-risk students.

In the future, big data approaches will become increasingly common in higher education, as they already are growing in other industries. These approaches will cross institutional boundaries, span K–20, and even link learning and workforce data sets. Our definitions will need to expand to encompass these emerging best practices.

**Extend student success to include learning, workforce, and life success.** A number of the institutions in our group of leading practitioners include employability and workforce issues in their institution-focused analytics efforts. Federal requirements for gainful employment reporting encourage such developments, which are expected to grow in the future.

Cloud-based analytics holds great promise for cross-institution and cross-sector analysis that will enable the extension of student success to include achievement of learning outcomes, preparation for employability, transitions between learning and work and back again, and workforce development.

Today, some practitioners are extending the definition of learner success beyond certificate or degree completion to include data on competences, employability, learning-to-work transitions, and even employment success. Future comparative studies and data mining are likely to combine learning and workforce elements and identify success-building behaviors and experiences. Today’s exemplary practices are the leading edge of these evolutionary developments. These practices include early life and career mapping tools as well as strong integration with national skills and competencies.

Examples of workforce applications include the following:

- LifeMap is Valencia College’s developmental advising system, promoting student social and academic integration and education and career planning, as well as acquisition of study and life skills. It creates a normative expectation for students that they have a career and educational plan early in their enrollment at Valencia and integrates a system of tools, services, programs, and people (faculty and staff) to engage with students to document, revise, and develop those plans.

- Northeastern University is very successful in student outcomes with their cooperative education (“co-op”) model. Approximately 92% of their student graduates are either
immediately employed or attend graduate school. They are striving to understand just why the model is so successful.

- The Minnesota State Colleges and Universities System uses analytics to understand workforce issues; it uses national skill sets data to develop course and degree pathways and to fit them together. A strategic direction in the new Charting the Future plan continues to focus on improving the alignment of workforce needs and education/training. See Charting the Future at www.mnscu.edu.

Many of the responding institutions suggested that workforce analytics was one of their next targets.

**From foundation to advanced practice.** Today’s pioneering efforts in using analytics to advance student success are setting the stage for even greater strides in the near future.

Analytics will be an essential future part of higher education. Institutions’ previous efforts of capturing data, providing availability in data warehouses, and initial data mining efforts are foundational to the next generation of activities. Higher education is benefiting from the extensive business intelligence efforts found in the corporate world and will develop new integrated solutions within the learning environment as one takes advantage of the LMS, SIS, and other emerging systems and applications.