
Learning analytics as a tool for closing the assessment loop in higher education

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Abstract: This paper examines learning and academic analytics and its relevance to distance education in undergraduate and graduate programs as it impacts students and teaching faculty, and also academic institutions. The focus is to explore the measurement, collection, analysis, and reporting of data as predictors of student success and drivers of departmental process and program curriculum. Learning and academic analytics in higher education is used to predict student success by examining how and what students learn and how success is supported by academic programs and institutions. The paper examines what is being done to support students, whether or not it is effective, and if not why, and what educators can do. The paper also examines how these data can be used to create new metrics and inform a continuous cycle of improvement. It presents examples of working models from a sample of institutions of higher education: The Graduate School of Medicine at the University of Wollongong, the University of Michigan, Purdue University, and the University of Maryland, Baltimore County. Finally, the paper identifies considerations and recommendations for using analytics and offer suggestions for future research.

Keywords: Academic analytics; Data mining; Data warehouse; Distance education; Higher education; Learning analytics; Online learning; Predictive modeling; Web analytics

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1. Introduction

Learning and academic analytics in higher education are used to predict student success by examining how and what students learn and how success is supported by academic programs and institutions. This paper will examine the role of learning and academic analytics and their relevance to distance education in undergraduate and graduate programs. It will focus on the measurement, collection, analysis, and reporting of data as predictors and drivers of departmental process and program curriculum. This process will inform a model of continuous improvement, which will be examined in the context of four institutions of higher education.

At its most fundamental level, learning is the result of interaction, and more specifically the result of engagement with the subject matter and often with discussions with others about that content. Learners interact with instructors, other learners, and with the course materials. Consequently, a learner may interpret these interactions based on his/her prior experiences and expectations and perform actions based on these interactions. Educators spend a tremendous amount of time preparing learning opportunities that maximize these interactions. They ask questions about the effectiveness of the course, whether it is meeting the needs of the students, if what is being done is working, and if not, whether it can be done better.

Typically, educators in post-secondary education have solicited answers to these questions when the course is over. The questions are most often part of end-of-semester course evaluations, which are self-reported, delayed, and often incomplete. As more resources and content are moved online, the amount of data available about these interactions delivers opportunities to examine, analyze, design, and deliver materials that can be used to make predictions about course and program effectiveness that respond to changing demands from students, instructors, and the administration. This is particularly true about distance education in developed countries where most interactions are facilitated and mediated using computer-assisted technologies (most frequently termed *online education* or *online learning*, used here for courses taught completely online or blended with in-person delivery), where data about these interactions can be captured about when, with whom, and with which content learners are engaging. In some cases, data and information are available that can help us to determine why and how students are connecting. Learning management systems (LMSs), content management systems (CMSs), and learning content management systems (LCMSs) make this process more streamlined and consistent, and at the enterprise-level many of them include built-in modules for discussion forums, social networking, and other tools supported by data collection mechanisms.

2. Analytics defined and contextualized

As is the case in any new area of practice and research such as analytics, many terms have been introduced that have inconsistent functional or conceptual definitions. Indeed,

the term *analytics* holds different meanings for different people (van Barneveld, Arnold, & Campbell, 2012). According to Long and Siemens (2011), presenting at the 1st International Conference on Learning Analytics and Knowledge held in 2011, *learning analytics* is the measurement, collection, analysis, and reporting of data about learners and their contexts, for the purpose of understanding and optimizing learning and the environments in which it occurs. These intelligent data systems can be used to improve teaching and learning as part of a process that is learner-produced, in proximity to the learning event. They can help to discover and reveal information and make connections at a course or program level that can in turn be used to make predictive models that can be used for academic analytics, which is the application of business intelligence in education and exists at an institutional, regional, and national/international level.

Campbell and Oblinger (2007) linked technological techniques to the administrative approaches to a larger scale: “Academic analytics marries larger data sets with statistical techniques and predictive modeling to improve decision making” with “the potential to improve teaching, learning, and student success”. Beyond learning and academic analytics, Campbell, DeBlois, and Oblinger (2007) predict that the current trends reveal that the graduation rates during this current information age are on course to reveal educational gaps, and a two percent decline in college degrees. While some differences may be made in definitions between *learning analytics* and *academic analytics*, in this paper these terms are used more or less synonymously.

As an emerging field, learning analytics relies on data culled from various sources to make decisions about academic progress, predictions about future performance, and to recognize potential issues (Johnson, Adams, & Cummins, 2012). Among the most significant challenges facing distance education has been the lack of knowledge about the ways that students interact with learning materials. Many of the characteristics of distance education that make it an appealing option for students, teachers, and administrators are the same features that make analyzing and evaluating course and program effectiveness a challenge. Because students are at-a-distance, educators do not get the same kinds of feedback from students (explicit or implicit) that they get in a conventional face-to-face classroom.

Web analytics is the process of measuring, collecting, and analyzing data related to user behavior on a web site and typically involves tracking user clicks. Until recently, it has primarily been used to gather data to evaluate products, processes, and actions by consumer groups to test the efficacy of marketing efforts. Opportunities for educators to receive information about how students in distance education programs use material and how they behave online opens realms where data-driven decisions can transform online learning environments. At a grassroots level, these opportunities can impact and influence academic environments, which can transform distance education programs through statistical techniques and predictive modeling. Initiatives informed by these various analytics will allow institutions and administrators to implement strategic initiatives that allow customizations to meet specific learning needs.

3. Processes and standards

The analytical process exists on a continuum of data and information that are transformed by the story that they tell about an organization. This transformation of information results from questions asked about the data that are captured and reported. Predictions are made based on various data types from a variety of sources. The challenge for analyzing distance education programs is compounded by a number of factors. Very little is known

about the ways students in the distance education classroom interact with materials, and the missing or incomplete feedback may make it difficult for educators and administrators to make decisions about whether materials need to be modified, discarded, or retained in their current state.

Distance education has continued to grow as the demand among learners, educators, and administrators challenge the expectations of the traditional and conventional classroom delivery. The tools and techniques used to evaluate and assess the value and efficacy of distance education are also impacted by rapidly changing technologies and techniques. As distance education has moved to the Internet, designers and developers ask questions about learners such as how they access the information, when they access the information, how they navigate through the materials, how long it takes for them to complete activities, and how they interact with the materials to transform the information into measurable learning. Web analytics provide a great opportunity for educators to obtain information about behavior and usage patterns among classroom participants. Historically, web analytics have been used as part of business-based marketing strategies that maximize computer tools to meet the needs of the consumer. The business-based approach has more recently been applied to students in distance and Internet-based education.

Campbell and Oblinger (2007) identify five steps of analysis: Capture, Report, Predict, Act, and Refine (p. 3). Decisions at the institutional level determine the key performance indicators of student success, which are then used to form the basis of operations reports that are used for decision making. Data may be taken in real-time from a LMS, CMS, or LCMS that integrates with a Student Information System (SIS), which may include additional information and demographics combined with historical and background information about student learners. These data may be stored under the purview of other locations on campus, such as financial aid, residential life, tutoring centers, and campus activities centers. Campus technology offices may also have access to information about student accounts that may provide additional information and data related to how students access and use campus technology and online course materials.

These pieces of data and information can be reported to key individuals to “identify trends, patterns, and exceptions in the data” (Campbell & Oblinger, 2007). Various data are used to make predictions about at-risk students, for example, so that analytics might be used to initiate an intervention designed to change student behavior and improve learning. Team members develop and review models to determine appropriate actions before the end of the course. Actions taken range from “information” to “intervention,” with determinations made about what to do, when to do it, and how often to do it that might generate more accurate models for measuring student success. This continuous improvement loop recognizes the refinement process that is informed by the delivery of new data that results from various factors, including participant behaviors, process improvement, curriculum changes, and other different actions (Campbell & Oblinger, 2007).

While the importance of continuous improvement is recognized, there is very little data and research available about the process. Several commercial products exist and use different technologies and business models; however, they generally do not apply directly to education models. Institutions of higher education use learning and academic analytics to identify predictors of student success. The underlying algorithms and parameters that drive data collection and reporting can be modified to refine the strategic focus in order to establish and enact interventions as needed.

The data collected are combined with statistical techniques to identify and describe technologies and methods used, analyze and evaluate the impact of activities and plans, and test and predict behaviors that can be integrated into a business process in keeping with academe. As many universities adopt a business-based approach to strategic planning, best practices, including those informed by web analytics will surely continue to transform the specific and often unique needs of higher education institutions. Academic analytics also provide institutions with the data that they need to make organizational and financial decisions. Goldstein and Katz (2005) identified the role that data warehouses serve in solving reporting and data needs in the context of several factors, including infrastructure support and decision making.

Dron and Anderson (2009) propose a “collective application” model to define learning analytics characterized by groups, networks, and collectives. In this context, the technologies support a cyclical process that support a continuous improvement model as information is gathered, processed, and presented. Gathering involves the selection and capture of data; processing involves the aggregation of information; displaying involves the sharing of the information; and dissemination involves decision-making based on that information. Dron and Anderson (2009) highlight a systems design that recognizes its inherent challenges and opportunities—not only of specific content and individual users, but also how the various and varied responses transform the role of the “collective”.

4. Tools and resources

Before any determination can be made as to whether any data-based analytics are effective, metrics should be identified that are meaningful, measureable, and monitored. In other words, any decisions about objectives and outcomes should be made in the context of an overall strategic plan. These analytics can be a powerful tool for discovering which modules, sections, or pages of a site are most popular and effective for learners. Additional data can be combined with learning analytics described earlier (e.g., demographics, academic ability/performance/history, financial, and other information) to make strategic decisions not only about a particular course section, but also about individual students and academic programs, and institutional planning.

5. Planning and implementation

The use of analytics in higher education is a relatively new area of practice and research. Attempts have been made to reach consensus on definitions, best practices, and areas of future research. The Horizon Reports of 2011 (Johnson, Smith, Willis, Levine & Haywood, 2011, p. 28) and 2012 (Johnson, Adams, & Cummins, 2012, p. 22) include learning analytics among the predictions to be in “mainstream use” in four to five years and two to three years, respectively. Several elements that make the collection of data and the analysis models that support learning analytics support the traditional and distance education classroom.

Institutions of higher education have made increasing demands on programs and courses to demonstrate student learning and their progression to degree. Learning analytics reveal data and information about usage, trends, and patterns of learning. Traditionally, student course evaluations provide data and information at the end of the semester, and have been based on openness and reflections of students who have completed the course. Learning analytics are collected before the end of the course, and can help to identify students who may be struggling during the course, and may include

feedback about how participants are using the course content, and their level of participation.

At the same time that the amount and kinds of data have increased, there has also been a rise in online learning and distance education. Large sets of data and data collected from different sources, with different standards and from users with different levels of access, reveal a fundamental challenge presented by incorporating data analyses into strategic planning. Institutions of higher education are increasingly called upon to measure, demonstrate, and improve student performance. Colleges and universities have deployed predictive modeling to not only examine learners in the classroom, but also predict course and resource utilizations, provide management to identify at-risk students, and make decisions about resource allocation and other decision-making and planning strategies at the institution level. The charge to institutions is to determine what data will support the strategic plan of the organization.

The needs and demands of participation in online realms can lead to confusion, technical problems, and loss of motivation. Instructors in this environment may not have the tools to know when students are not engaged with course materials because they are bored, confused, or overwhelmed. While an LMS provides some built-in capabilities for tracking some student activities, additional reporting and visualization tools and features can be incorporated into a data-based strategy to supplement those data collected with an LMS. This strategy should also include a process to gather, track, and analyze the significant amount of data that represent student activity that occurs outside the LMS. The challenge then becomes how to extract meaningful data from varied and disparate sources.

The data that are collected, reported, and analyzed draw attention to the various groups that are impacted by the changing spheres of learning and academic analytics. Learners, instructors, institutions, and regulatory agencies have overlapping interests that require different kinds of data collection and reporting, which in turn have impact on how institutions capture data, report findings, make predictions, design and develop strategies, and refine models. Decisions about whether to use an enterprise-level solution or to develop their own, or even to design a system that uses a combination of each, should be the result of deliberate and focused discussions where all stakeholders (including administration, faculty, staff, and students) share goals, ideas, experiences, and best practices. Following are examples of four working models from higher education institutions.

6. Examples and practice

This paper presents some of the major analytics initiatives to date and how they are helping to establish a culture that is moving from “information and reporting” to one that informs and enables action (Norris, Baer, Leonard, Pugliese, & Lefrere, 2008). This section shares information about the solutions implemented by four institutions, and the different approaches they have taken to understand the data and information they have collected on and about their students, and how they have used these data to make informed decisions about program content and course delivery. They include the Graduate School of Medicine (GSM) at the University of Wollongong, the University of Michigan, Purdue University, and the University of Maryland, Baltimore County.

6.1. Graduate school of medicine at the University of Wollongong

The Graduate School of Medicine at the University of Wollongong uses academic analytics throughout the development and implementation of its distinctive, outcomes-based curriculum, which is taught using clinical problems, the body systems to which these relate, and case studies. The curriculum also requires that students begin work at hospitals and in general practices within the first six weeks of beginning study. Because the curriculum consists of on- campus and off-campus elements, it is easy for the delivery of the course to become disjointed. GSM collects information and data about clinical placements over the course of their medical school training. Their tool was developed to allow students “to record their experiences and reflections, as well as enabling the school to support them in integrating their experiences to the curriculum” (Olmos & Corrin, 2011, p. 934).

GSM uses an LCMS, Equella, to collect and store all learning and teaching resources. Equella captures patient demographics, the presenting complaint mapped to the curriculum’s case studies, and the students’ placement location. This information is tagged as metadata and exported as XML-formatted reports that are used to create data visualizations. It is also used to track the students’ level of involvement (observation, examination, etc.) and their self-reported confidence level during their rotation assignment. Students identify learning needs and required actions. GSM administration uses these data to ensure the quality of the curriculum by ensuring the coverage of content in the curriculum and supporting the engagement of students during regional/rural clinical placements (Olmos & Corrin, 2011).

6.2. University of Michigan: E²Coach

Nationally, more than half of students who enroll in Science, Technology, Engineering, and Mathematics (STEM) disciplines fail to complete their degrees (McKay, Miller, & Tritz, 2012). The University of Michigan designed E²Coach, a student support and intervention system that originated from the collection of information about the progress of nearly 49,000 introductory physics students over a period of fourteen years. It provides a model for an intervention engine that identifies strengths, weaknesses, and performance trends that impact student success in completing their degrees. E²Coach identifies at-risk students by initially collecting data from study group leaders, physics professors, and from the students themselves. These data allow the construction of predictive models of student performance.

E²Coach provides the interface between students and the resources available to them by offering customized recommendations that suggest study habits and practice assignments and delivering feedback on progress and also encouragement in an effort to maximize each student’s success (McKay, Miller, & Tritz, 2012). E²Coach advice is also delivered to each student on a web page that is tailored and personalized. Advisors are study group leaders who have successfully completed their STEM-related degrees, and they are matched with current students based on shared backgrounds and goals. The ability to customize advice and support for each student is made possible by leveraging an existing and proven open-source tool, the Michigan Tailoring System (MTS), which was developed by the University of Michigan Center for Health Communications Research (CHCR). A distinct advantage of this program is its scalability and extensibility.

6.3. Purdue University: Signals

Purdue University began considering the use of academic analytics as a way to improve the student experience in 2003, which became a cornerstone of its strategic plan (Arnold, 2010). Its initial foray into analytics was the Purdue Early Warning System (PAWS), which focused on engaging instructors to identify at risk students in order to provide them with instructional support services. Although somewhat useful, PAWS had some limitations. For example, warnings came too late in the semester to benefit students, and they were not tailored to include resources for specific courses.

At this juncton, a group of IT professionals began work on the Signals analytics project. Introduced in 2007, Signals mines data from an SIS, a CMS, and the grade book and is based on a statistical student success algorithm (SSA) developed by Purdue's John Campbell that can identify each student's risk level (Arnold, 2010). Purdue's premise is that student success is based on student aptitude, as measured by standardized test scores, and student effort, as measured by participation in the CMS (Campbell, DeBlois, & Oblinger, 2007). The goal of Signals is to flag at-risk students based on demographic information and grade performance, as well as student behavior and effort by posting a traffic signal indicator (i.e., red for high risk of failure, yellow for moderate risk of failure, and green for low risk of failure) on the student's CMS home page. Instructors can use Signals at their discretion to help struggling students change their behaviors in order to improve their grades. Instructors who incorporate Signals into their courses can customize an intervention schedule, which can include e-mails and reminders, text messages, referrals to academic advisors, help desks, or academic resource centers, and requests for face-to-face meetings. According to Arnold (2010), Signals has generally been met with positive reviews by students, faculty, and administrators alike, and empirical data has validated its impact. Data collected during the pilot of Signals from fall 2007 through fall 2009 indicate that students using Signals "earned 12 percent higher levels of B and C grades in sections using Signals than in control signals that did not, as well as 14 percent lower levels of D and F grades" (Arnold, 2010, p. 5). Also, students who were identified by Signals as high risk generally took action to address behavior issues in order to become more successful in the class.

It should be noted that instructors did express some initial anxiety that they would be met with an overwhelming number of students seeking help, but this has not been the case. Another concern expressed by faculty was that Signals would create dependent behavior in new students rather than "the desired independent learning traits" (Arnold, 2010, p. 7). As Signals continues to evolve, more attention will be paid to the establishment of best practices for using the tool in order to address concerns and promote its value as an analytics tool.

6.4. The University of Maryland, Baltimore County

The University of Maryland, Baltimore County (UMBC) collects and manages data and information about students as part of an integrated strategy for teaching, learning, and technology (TLT) (Trinkle, 2005). Trinkle's 361° model introduces the importance of aligning strategic goals by "using technology to enhance liberal arts education and enrich the college experience". Among the key factors for success outlined in this model is the alignment of technology with the mission and culture of the institution, which is accomplished by actively involving students in the utilization of technologies that reduce barriers and create a community of learners. Goldstein and Katz (2005) examined the role that timely information plays in a successful implementation of the management of

academic analytics, and identified three dimensions of technology performance: to provide timely access to data, to make information widely accessible, and to ease the use of the technology tools.

UMBC uses Blackboard LCMS to support key areas of its strategic plan, which identified student learning outcomes, infrastructure support, and online/hybrid learning strategies among its key objectives. Functional and technical questions were identified to construct a predictive model of student performance. Early Blackboard reports (in 2008) showed faculty how many times instructors and students were accessing course materials (“Check My Activity,” “Grade Distribution,” and “Tool Usage”). These data could be compared to each other, and to overall use. Initial findings suggested that students who earn higher grades use Blackboard more often than students who earn lower grades. Data queries were run against either a static or cached copy of the system by a manual process, and the load on the system would sometimes cause unanticipated crashes. Once this problem was isolated and understood, a plan was put in place to support daily backups of data.

Timely and personalized feedback about activity when compared to an anonymous summary of the same data about their peers can be used by students to change their behavior about course concepts, materials, instructors, and each other. By 2010, UMBC integrated data using the campus’s iStrategy data warehouse to extract data from Blackboard (activity) and Student Administration (grades, demographics), combined with Google Analytics, to examine individual student activity and grade distribution. Proposed changes to Check My Activity include integration of these data with UMBC’s “early alert” system if student’s grades fall below a certain grade or grade point average (GPA), and updated features and a better graphical display. Currently, instructors can look at most active courses, active courses by discipline, i.e., all courses and all activity (Fritz, 2012).

UMBC offers several distance education programs, including Emergency Health Services, Information Systems, and Instructional Systems Development, all of which use Blackboard to deliver some or all content. Key course sections are also delivered at-a-distance synchronously and asynchronously. UMBC utilizes Blackboard’s Adaptive Release (ADR), a feature which allows instructors to control the release of specific course content by several factors: date and time, individual users, group membership, scores or attempts on any Grade Center item, calculated columns in Grade Center, or review status of an item in the course. Best practices for ADR and all features are introduced to instructors during a series of “Effective Practices” workshops (Fritz, 2012).

Hrabowski, Suess, and Fritz (2011) examine the role of “transformational initiatives” at UMBC in the context of developing a “culture of assessment.” The role of leadership to “help create the vision, set the tone of the climate, emphasize the values that are most critical, and build trust among people”. Information technology supports a campus culture where decisions are made that support strategic goals, and provide data gathered from different sources. Collaboration with other key officers on campus, including Institutional Research, help to identify critical factors of success and ask questions that can be answered by data collected from LMS data, which is integrated with data warehouse and other key demographic data.

7. Considerations and recommendations

Several research considerations should be addressed by academic institutions that seek to incorporate web analytics with learning and academic analytics. The Table 1 below

outlines some considerations associated with the implementation of an analytics project in distance education and offers recommendations for addressing them. It is important to note that many of the considerations stems from the fact that analytics is a tool under development, part of an emerging field that will likely evolve dramatically in the near future.

Table 1

Considerations and recommendations for implementing analytics projects

Considerations	Recommendations
Strategic Planning. Define clear objectives and outcomes and make decisions about project goals. Administration should establish a strategic plan that specifies the process, the procedures, and assigns responsibilities for key roles.	Draw formative feedback and analytics from a range of scholarship related to how students learn, what motivates them to learn, and what factors influence effective learning.
Big Brother. Not all faculty and/or students will welcome the tracking of individual behavior and actions within a software application. They may be uncomfortable with how the decisions are made with regard to how the data collected are being used (Campbell, DeBlois, & Oblinger, 2007).	Provide an option for an individual faculty member and/or student to opt out of an analytics project. Access and security, including privacy issues and concerns, will be addressed. Establish best practices to inform faculty and/or students about the impact of analytics on their performance and the implications at the course and program levels.
Expertise. In some academic institutions, several offices or departments may be responsible for various aspects of the analytics project without one overseeing and taking ownership for data assessment and intervention. For example, an institutional research department may be responsible for data collection and reporting, whereas an IT department may be responsible for the technical infrastructure. Problems can arise in coordinating analytics efforts and identifying the appropriate people to analyze and assess the data, and ultimately make recommendations for implementing interventions.	Designate one office or department to oversee the interdisciplinary team participating in analytics projects. Key stakeholders from designated offices will be included in all relevant decision and policy making. Other considerations may include the development and monitoring of data and data integrity issues. Determine what expertise is needed for individuals who will respond to alerts with appropriate interventions.
Presentation. Data should be depicted in visuals that are readily interpretable. Managers want access to concise visual summaries of data, not lengthy reports. They need confidence that they are looking at a certain snapshot in time that can be compared appropriately with other snapshots in time. In addition, data can display problematically based on the	Develop the methods and tools to present analytics and visualize data. Dashboards should be easy to use and understand and be customizable to permit changes of roles and contexts as needed. Recommend one browser for viewing data visuals so that the visuals display correctly.

browser used.	
Standards. Datasets often exist in silos. Tools should be developed that can extract and aggregate data from various datasets residing on multiple platforms in order to facilitate data sharing among researchers.	Adopt structure and best practices to allow tools to be used across multiple platforms to support data sharing. This may also include changes to data warehouse reporting environment and to specific reports. These datasets will also be used by researchers who will assess reliability and validity of the models used.
Investigation. These days more people are learning informally as opposed to formally. How can data for analytics be culled from devices that are used for informal learning (e.g., clickers, social networks, and others)?	Explore opportunities for adopting new technologies, such as mobile. Consider also informal learning options that may exist outside formal settings within academe.
Identification. The data warehouse should only be available to others on a need-to-know basis. Problems arise when data are misused for unauthorized purposes, e.g., when people do not have permissions, do not understand the data they're looking at, and do not understand its appropriate use. Also, some people access the data without having the best intentions.	Develop procedures and policies regarding ethics, privacy, ownership of data, and best practices.
Training and Development. The implementation of data collection, reporting, and analysis necessitates a plan to accommodate the significant increase in data and systems users. These data users may have different needs and levels of expertise.	Face-to-face training and on-demand training (via help desk ticketing and knowledgebase) should be developed for different levels of users. This may also include a "user support group" that meets regularly to discuss system upgrades, and changes in reporting structure.

8. The future and other considerations

Distinctions are made about how different levels of data collection and reporting are performed based on how the data will be used—web analytics/data mining as a technical challenge; learning analytics as an educational challenge; and academic analytics as a political/economic challenge. The connections among these levels reveal opportunities and challenges of learning, including social contexts. During the past decade, LMSs have been adopted by a large number of higher education institutions, with the recent addition of several social networking and cloud-based technologies, some of which have recently been incorporated in enterprise-level LMSs. The integration of collection and analysis of data from a variety of sources facilitates retrieval and analysis of data to allow individuals and institutions to make informed decisions about allocating resources and enabling interventions that promote successful learning strategies.

Automated methods may be used to examine metadata about experience, motivation, and learning. Key stakeholders in an academic organization include faculty, students, executive officers, student affairs staff, institutional research staff, and information technology staff (Campbell & Oblinger, 2007). Each group impacted by these analytics projects make predictions based on these data and how they will be used. They will also offer insight into behaviors and suggest interventions to support student success. These inputs will inform a model of continuous improvement that seeks to close the loop of objectives and outcomes for programs, courses, and activities.

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