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Guiding Early and Often: Using Curricular and Learning Analytics to Shape Teaching, Learning, and Student Success in Gateway Courses

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2. *This chapter provides information on how the promise of analytics can be realized in gateway courses through a combination of good data science and the thoughtful application of outcomes to teaching and learning improvement efforts – especially with and among instructors.*

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The emergence of analytics in higher education institutions is a relatively recent occurrence. While the corporate world has used the nomenclature "business intelligence" for decades, analytics as a term, much less a process, was not used in colleges and universities until Goldstein and Katz (2005) put forth "academic analytics" for the first time (Oster, Lonn, Pistilli, & Brown, 2016). Bischel (2012) defines analytics as "the use of data, statistical analysis, and explanatory and predictive models to gain insights and act on complex issues" (pg. 6). Essentially, the goal is to learn things not previously known and take action on outcomes in an effort to improve.

There are varying levels of analytics (see van Barneveld, Arnold, & Campbell, 2009) described within higher education. Some address the whole institution, some look to predict outcomes, and others look to prescribe select actions that may address various problems and challenges on campus. The specific focus of this chapter is on learning analytics, which focuses on "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Society of Learning Analytics Research, 2012).

Effective use of learning analytics begins by using relevant data to identify those courses in a curriculum where improvements in learning will yield improved outcomes throughout an entire degree program. That is, it is important to identify early courses in a curriculum that are considered foundational in the major. Improved student success in these gateway courses provides a vital catalyst towards successful degree completion. Thus, the insights gained through curricular analytics should spur actions that lead to beneficial change at the individual course level. Finally, the "loop" around the improvement efforts is closed by collecting additional data for assessing the impact of changes and to drive additional improvement efforts (Clow, 2012).

Learning analytics holds great promise with regard to creating personalized approaches to learning (Siemens, 2012) or moving education into a space where predictions of student performance can occur (Kellen, 2013), resulting in targeting specific enrichment, tutoring, or supplemental resources to individual students. Lockyer, Heathcote, and Dawson (2013) note that the teaching and learning environments are improved through the use of learning analytics, in particular through the redesign of curricula as a result of examining what is and isn't working (Dunbar, Dingle, & Prat-Resina, 2014), and by evaluating the likely impact of possible redesign efforts. Through the improvement of the environment, we are able to demonstrate increases in student performance (Arnold & Pistilli, 2012; Dietz-Uhler & Hurn, 2013; Gray, McGuinness, Owende, & Hofmann, 2016) and student learning (Clow, 2013). As Pistilli, Willis, and Campbell (2014) write, "the institutional application of analytics can result in a major shift for colleges and university with regard to the culture fostered around undergraduate learning" (p. 88).

This potential for change, however, requires an institution to be ready to move into a realm of data-driven change. Arnold, Lonn, and Pistilli (2014) assert that readiness must be a shared concept understood by individual institutions seeking to create the greatest opportunity for successful implementation. Oster et al. (2016) go further, describing readiness as "a necessary condition for institutions to be able to perform educational functions consistent with their individual missions … particularly towards student success" (p. 174). The reflective process that Arnold et al. (2014) and Oster et al. (2016) propose is one that any institution should consider using, as it has the potential to produce a great deal of organizational learning involving large swaths of the university community.

While there is a need to describe what analytics is, and a need for campuses to be ready to implement learning analytics, we also believe that a brief discussion of what analytics *is not* is in order. Analytics in general is not just a fad in higher education; Gartner first included analytics in its annual "hype cycle" in 2007 (Fenn & Lincoln, 2007), and the marketplace for learning analytics tools is becoming more and more saturated.

Additionally, analytics is not a solitary process; as Oster et al. (2016), Pistilli et al. (2014), and others describe, multiple staff participants from across many different facets of an institution are needed to implement analytics effectively. Finally, as Arnold and Pistilli (2012) note, the development of a learning analytics solution at any given campus does not have to involve complex algorithms that only statisticians and econometricians understand; Purdue University's *Course Signals* (described later in this chapter) was first developed using Microsoft's Excel and IBM's SPSS products.

Applying Learning Analytics to Gateway Courses

Introductory courses, whether large- or small enrollment, often pose challenges to students. These are usually the courses students new to college encounter in their first semesters of study, and tend to be the foundation for learning that will occur over the ensuing years. The inability to pass an introductory course in a given discipline precludes a student from taking additional courses within that discipline. Thus, we can think of the introductory courses in a student's major as the most important in terms of their impact on progression toward a degree.

The challenge comes when students begin to struggle in these courses—for example, students who have never needed to put a great deal of work into their studies in the past. Further, faculty are often charged with improving outcomes in given courses—that is, ensuring that students are both learning and that non-passing rates are held to a minimum (McCray, DeHaan, & Schuck, 2003). These same faculty also want to see students succeed in their work; few faculty go into the classroom to ensure students don't pass. DeBrew and Lewallen (2014) noted that faculty "find that failing a student is stressful" (p. 631) and, as such, would rather avoid having to do so. Faculty obstacles are often related to size and scope – with how many students one should intervene and how one should do it effectively and efficiently. In the end, institutions usually seek the same ends as students and faculty – improved learning, improved outcomes, and increased use of resources available to students on campus (Macfadyen & Dawson, 2012). As such, we now will discuss student-, faculty- and institution-focused reasons for implementing curricular and learning analytics.

Student-focused reasons. The primary change in students who graduate from high school in the spring and start college in the fall is that they are about three months older. Further, during those three months, typically nothing magical happens to make those students self-regulated learners who are acutely aware of how their actions or inaction affects the end-of-term outcomes for a given course. Learning analytics may be one way to help new college students develop self-regulation (Siemens, 2012), enhance their understanding of their standing in a course (Fritz, 2013), and, ultimately, improve their own learning and performance (Picciano, 2012). Curricular analytics can be applied to determine the impact these course-level improvements will have on overall success rates.

Help-seeking behavior. At its core, help-seeking behavior is rooted in student self-regulation and hinges on students' seeking assistance when they need it from appropriate sources (Corrin, de Barba, & Bakharia, 2017). Baker and Corbett (2014) describe a learning environment in which students are assessed not only on their learning of course material, but also on their ability to improve "skills that cut across domains, such as … help seeking" behavior (p. 39). The use of learning analytics can promote this behavior through interventions such as emails, texts, or phone calls. However, Pardo, Han, and Ellis (2016) caution that if students are not self-regulated enough to take action on feedback, any intervention employed may be unsuccessful; as such, instructors can use learning analytics-driven interventions (and in-class opportunities) to help students understand the need to visit office hours, attend help sessions, and utilize subject-specific resource rooms on campus (Gray et al., 2016).

Enhancing students' understanding of performance. Students who understand how their own behaviors relate to their performance have a better chance of being able to alter what they do in an effort to improve their grades. Learning analytics provides an opportunity for giving students feedback about their learning processes. Feedback is defined as an exchange between two or more persons in an effort to better inform individuals' knowledge about their performance, their relative position in a course, and how to enhance their individual work (Tanes, Arnold, Selzer King, & Remnet, 2011). Feedback is beneficial for students, increasing students' self-regulation and intellectual curiosity as well as guiding learning goal setting and their achievement (Gray et al., 2016).

Enhancing faculty's understanding of success. Programs that understand how their curricular structure affects student progress have a better chance of being able to provide resources within particular key courses that allow student to overcome obstacles to success. Curricular analytics tools can help programs become more aware of the inherent difficulties and bottlenecks within a curriculum and can serve as a guide as to how to apply limited resources most effectively within a curriculum. Furthermore, faculty are more likely to make use of learning analytics within their own courses if they have a big-picture view of how these course-level improvements will impact the overall success of their program.

In order to understand how improvements through learning analytics at the individual level will impact the success of a course and how this will ultimately impact student success within a program, faculty must have access to aggregate data and statistics. By applying the appropriate analyses to this aggregate data, faculty can gain a better understanding of when and why particular student populations leave a program, thereby allowing them to focus improvements related to learning analytics on the courses most likely to improve overall success outcomes. Below we describe two applications, Curricular Analytics and Student Flow Diagrams, that have proved useful in this work.

Faculty- and institution-focused reasons. While the primary reason for implementation of learning analytics by an institution is likely to improve student success, there are other compelling reasons for using learning analytics, especially when it comes to improving outcomes in gateway courses. This section briefly examines some of those reasons, including increasing faculty-to-student communication and improving course outcomes.

Increasing faculty-to-student communication. Chickering and Gamson (1987) describe faculty-to-student communication as one of the best practices associated with undergraduate learning, noting "faculty concern helps students get through rough times and keep on working" (p. 3). Student success literature holds many discussions regarding the fact that the greater the amount of interaction between students and faculty in the first year of college, the greater the likelihood of persistence to a second year of study. Tanes et al. (2011) also found that faculty who engaged with students using learning analytics saw greater foot traffic during office hours, wherein questions could be answered and guidance provided regarding how to study, what to review, and, if necessary, whether a course should be dropped before the student earned a failing grade. It can also be argued that through providing additional information to students, faculty are able to ensure that students are learning more of what is being taught. In the end, there are few negative effects for students who experience increased contact with their faculty.

Improving course outcomes. In the same vein of increased student performance comes the improvement of course outcomes. Booth (2012) notes that learning analytics is, in fact, a way to both measure and support learning, and, further, Gašević, Dawson, and Siemens (2015) remind us that learning analytics are about learning.

It stands to reason that if more students are able to successfully complete a course, then the overall outcomes for the course will increase as well. Macfayden and Dawson (2012) and Arnold and Pistilli (2012) both demonstrate increased course outcomes through the application of learning analytics – in particular, providing feedback to students indicating what they could do to improve their grades. Dietz-Uhler and Hurn (2013) also describe how learning analytics can validate faculty members' intuition about student performance and provide a vehicle for intervening in a timely manner – resulting in improved learning, higher success rates, and increased student persistence towards graduation.

Putting the Action in Actionable Intelligence

Pistilli et al. (2014) assert that learning analytics has the potential to move colleges and universities "from simply understanding various data points and their intersections, to using them to create actionable intelligence" (p. 80). They continue, however, noting that it is imperative that institutions and faculty take "action on that intelligence as a means of positively affecting one or more behaviors" (p. 80). The most direct action that can be taken is to provide feedback to students, which Astin (1993) notes is something that can improve students' cognitive and personal development, especially if it is fair and encouraging (Lizzio & Wilson, 2008), as well as actionable (Pistilli et al., 2014).

Simply providing feedback is insufficient; feedback must be given both early and often – early enough in the term where students are able to take action to correct behaviors and improve performance, and often enough for them to see the fruits of their labors (Wise, 2014). Chickering and Gamson (1987) describe frequent communication with faculty as one of the seven principles of good practice in undergraduate education. Draschler and Greller (2012) also indicate that the potential for increased faculty-to-student interaction is one of the greatest outcomes associated with learning analytics.

Feedback provided, however, must be explicit and emphasize outcomes rather than past behaviors (Tanes et al., 2011). It must also be timely; that is, direction needs to be provided to students while they can still employ it (Wise, 2014). At the same time, the tone and rhetoric employed must convey concern for students and be constructive in nature (Lizzio & Wilson, 2013). Feedback also should be brief (Tanes et al., 2011). Failure to observe these conditions may result in students deeming feedback ineffective or ignoring it altogether.

Learning analytics application examples. Several institutions have had success in developing and implementing learning analytics solutions that have increased student success and overall outcomes – in particular, but not limited to, gateway courses and other large enrollment classes. This section highlights several of those initiatives.

Check My Activity. Check My Activity is a tool built into the University of Maryland Baltimore County's learning management system (LMS) (Fritz, 2013). Faculty using the tool allowed students to see how often they logged into the LMS as compared to their peers, their grades, and the general grades for those who had more or less interaction with the LMS than themselves. Students then used the information presented to them to change their approaches to studying, completing work, or seeking assistance, actions that resulted in higher grades.

Course Signals. Developed at Purdue University and later licensed to Ellucian, Course Signals was one of the first learning analytics tools deployed at scale. As Arnold and Pistilli (2012) describe, "the premise behind [Course Signals] is fairly simple: Utilize the wealth of data found at an educational institution, including the data collected by instructional tools, to determine in real time which students might be at risk, partially indicated by their effort within a course" (p. 267). The tool provides faculty members with a way to reach students in three different categories of risk – high risk of doing poorly in a course, moderate risk of poor performance, and low risk of poor performance – and provide guidance and directives to help maintain or improve their grades in the course.

Curricular Analytics. Based upon analytical methods developed by researchers at the University of New Mexico (Heileman, Hickman, Slim, & Adballah, 2017), the university created a curricular analytics website (curricula.academicdashboards.org). Via this website, users are able to upload the course and prerequisite details associated with a curriculum. The curriculum is then analyzed in order to determine the most crucial courses in the curriculum, along with the complexity of the curriculum as a whole. An interactive graphical representation of the curriculum is provided, allowing users to investigate individual curricula, evaluate the impact of possible curricular changes, and compare similar curricula at different institutions.

E^2Coach. E^2Coach, developed by researchers at the University of Michigan, provides an "interface between students and the extensive and powerful resources available in each course, customizing recommendations for study habits, assignments for practice, feedback on progress, and encouragement they receive" (McKay, Miller, & Tritz, 2012, p. 90). The tool delivers personalized feedback to students with information on their work,

comparison against their peers' performance, and predictions of final grades should students continue to exert the same effort for the rest of the term.

Student Flow Diagrams. This tool, developed by researchers at the University of New Mexico (Heileman, Babbitt, & Abdallah, 2015), displays a Sankey diagram that represents the flow of students from a given cohort through a college or university system. The application also allows users to drill down into individual colleges, departments, and programs in order to see how students flow through these units. Through the visual explorations provided by this tool, deductions can be made about success or failure areas of individuals or cohorts of students as they progress through a program. See studentflows.unm.edu for an example.

Implications and Considerations

The student success imperative is driven by a number of factors that demand our attention, and, at the same time, necessitate careful use of analytics to inform improvement efforts. First, unlike a generation ago, a college degree is now more likely to serve as a precondition to meaningful employment. This has led a significantly larger percentage of high school graduates to now enter college, leading to a much more extensive set of learning needs and student success challenges on college campuses.

Second, as the ability to obtain a college degree has grown in importance, higher education has perversely become much less affordable to most students. The reasons for this are myriad, and well beyond the scope of this chapter, but the net effect is that tuition, books, and room and board costs now routinely add up to more than $25,000 at even low-cost public colleges, and students are leaving college with unprecedented levels of debt (Heller, 2013; The Institute for College Access & Success, 2016).

Thus, we are confronted with the need to serve a broader population of students, with more significant consequences if there is failure at any step in the student journey. In the past, if students failed a class and lost a scholarship, they may have had to work over the summer to earn additional income, or take on a few thousand dollars of additional student debt. Today, for many students, a delay in graduation by one year can mean $20,000 or more of additional debt, and the loss of a scholarship is a financial catastrophe that often precludes continued enrollment in college.

For these reasons alone, alongside many others not discussed in this chapter, institutions must strive to better meet the needs of their students. This begins by working to gain a more holistic understanding of how the structure of a curriculum affects the specific populations of students attempting to complete that curriculum. From this we must work to identify those gateway courses that have the largest impact on student success, and then apply learning analytics to empower the success of the students in these courses. In this way, through a judicious use of data science applied to curricula, and a thoughtful application of these outcomes to teaching and learning improvements, the promise of analytics in higher education is realized.

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