Navigating Learning Analytics in Higher Education

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Abstract

Although learning analytics is a growing movement within higher education, it can be difficult for faculty as well as those who provide pedagogical design and support (i.e. educational developers, center for teaching and learning professionals) to keep up with the literature surrounding such an evolving field. This paper describes the emergence and definition of learning analytics and summarizes current uses of learning analytics through three categories: descriptive, diagnostic, and predictive. The authors also discuss needs and challenges of learning analytics for a range of higher-education stakeholders, including academic administrators, faculty members, front-line administrators, and students. An exploration of the data literacy needed for each of these stakeholder groups is also provided. After reading this paper, faculty and pedagogical design and support professionals will have a better understanding of what learning analytics are, as well as ideas for how they might utilize this technology to improve student outcomes.

Keywords: Learning analytics, predictive analytics, assessment, evaluation, faculty, pedagogical design and support professionals

Navigating Learning Analytics in Higher Education

Analytics is the formal discipline in IT for methodically doing data collection, filtering, cleaning, translation, storage, representation, processing, mining, and analysis with the aim of extracting useful and usable intelligence. (Raj, Raman, Nagaraj, & Duggirala, 2015, p. 70)

Learning analytics is 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. (Siemens & Gašević, 2012, p. 1)

A recent EDUCAUSE article referred to analytics (including but not limited to learning analytics) as "one of higher education's top IT-related issues" (Arroway, Yanosky, Brooks, Thayer, & Morgan, 2015), and learning analytics (or "analytics technologies" as listed in 2018 and 2019) were included in six of the past eight years of the EDUCAUSE Horizon report as a key technology development (Alexander et al., 2019). In addition, the Bill & Melinda Gates Foundation has named learning analytics as a "next generation strategy" (http://nextgenlearning.org/topics/learning-analytics). Clearly, then, learning analytics has come to play an important role in the higher education learning landscape.

Due to advances in technology that can store big data (Dillon, Wu, & Chang, 2010), broad availability of learner data has grown since the 2000s. Consequently, the kinds of data and the areas where data-informed decision-making is applied have stretched across the higher education enterprise. At the same time, the concept of analytics, the roles of the data collected via analytics, and the stakeholders who are involved in owning and managing data, among many other factors, are still being explored and discussed across higher education institutions of all types (e.g. Leitner, Khalil, & Ebner, 2017; Slade & Prinsloo, 2013). Although using data to make informed decisions is not new to higher education, what has changed is the scope of the data available and the urgency for decisions to result in timely (one might say immediate) improvements in a number of areas, most notably student academic performance, retention, and graduation rates. The vast amount of data and new technological tools (e.g., artificial intelligence) available, rather than traditional ideas of assessment or metrics, are driving the current conversation about analytics and the promising possibilities that employment of analytics creates.

While many are engaging in this conversation about analytics, professionals whose primary responsibilities focus on designing or supporting pedagogy may find it difficult to keep up with the literature surrounding learning analytics in higher education. The current paper provides a concise explanation of the emergence of learning analytics, as well as discusses potential uses of learning analytics, stakeholders involved, and data literacy needed. This paper can be used a as a resource for faculty, educational developers, center for teaching and learning staff, and other professionals who wish to understand what learning analytics are and how they may use learning analytics in the future.

The paper is organized into four major sections. First, we describe the emergence and definition of learning analytics. Second, we summarize current uses of learning analytics, using practical examples. The third section discusses the learning analytics needs and challenges of a range of stakeholder groups in the higher education environment, and the fourth section provides data literacy information for each group. Taken together, content contained in these four sections should provide pedagogical design and support professionals with information that may generate ideas about how they could utilize learning analytics within their respective roles and institutions.

The Emergence of Learning Analytics

In its most promising form, analytics help us to understand trends and underlying patterns that are derived from extremely large, complex, and interrelated sets of data. In just a few short years, many in higher education have innovated to address the need to more effectively collect, store, connect, and analyze the millions of data points being generated and available for use. The resulting challenge for analytics in higher education is in determining how to organize, integrate, and develop inferences from those volumes of data in order to expand the relevant information available to the university community, fine-tune current data use and collection processes, and add nuance to academic decision making through analytical rigor.

Analytics in general, or the process of extracting data for application, had been utilized by sciences such as physics and biology since as early as 1970 (Baker & Inventado, 2014). However, the use of analytics for educational purposes has been more recent; for example, educational data mining (EDM) emerged in the 1990s (Romero & Ventura, 2007), and other forms of analytics quickly developed points of divergence. Although a thorough comparison of each form of analytics falls beyond the scope of this discussion, one way to conceptualize the scope and aim of each approach may be understood as follows:

- Educational data mining applies machine learning and data mining techniques to large sets of educational data with the intent of displaying data patterns that could potentially be useful. In its focus on standardizing data and analytical methods across systems, EDM considers the technical challenge of extracting value from large sets of learning-related data (Ferguson, 2012; Romero, 2010).

- Academic Analytics employs tools to assist with analyzing and visualizing data in order to help education leaders understand trends in instruction, learning, and student progress. According to Ferguson (2012), academic analytics focuses on the political and economic challenges of enhancing learning opportunities and improving educational results, such as retention and graduation rates at institutional, regional, and/or national and international levels.

- Learning Analytics narrows the focus of these data and analyses to the specific activities and interactions involved in learning itself. LA employs visualizations and analyses of course-level and department-level data to benefit students and instructors and to shape pedagogical and curricular decision-making. The goal for data produced by and collected about students' behaviors is to use that understanding to improve learning (Khan & Pardo, 2016; Clow, 2012).

(For an excellent overview of the rise of these fields and specific emergence of learning analytics, see Ferguson, 2012.)

One enabling condition for the development of LA—and a major factor in the timing of its emergence—has been technological advances that make it possible for educators to track and record exchanges and interactions occurring within the teaching and learning experience (Dillon et al., 2010). Data resulting from behaviors that can be collected and interpreted originate from a variety of sources, including engaging in activities in a Learning Management System (LMS). Examples include such learner behaviors as accessing modules, completing and submitting assignments, and adding comments to a discussion board; completing online homework and quizzes through online content providers (including publisher, faculty member, or university developed digital content and tools); sending quiz responses collected via personal response systems (e.g., clickers, Learning Catalytics, etc.); or browsing an Open Educational Resource (OER). Data collected through a student's digital footprint offer the promise of authenticity, accuracy, and immediacy not available in prior decades or via other methods.

Previous methods for gathering information, such as interviews and surveys, combined user perception and opinion with accounts of their behaviors. However, the methods were time-intensive and fundamentally narrow in scope due to their reliance on samples rather than complete cohorts. What is perhaps most attractive about mining data automatically collected as users simply conduct their daily routines is that such data reflect "real and uninterrupted user behavior" (Greller & Drachsler, 2012). In regard to the technological capacity of educational institutions, this variety of sources has resulted in complex data sets of ever-increasing size. Although many institutions worldwide have taken steps to accommodate the scope of data, they nonetheless face the more daunting and important challenge of synthesizing the disparate data points, making meaning of them, and then visualizing and reporting on them in useful ways (Ferguson, 2012).

Although Learning Analytics discussions emerged most actively in fields such as distance education and technology-enhanced learning research, since 2012 LA and discourse on student and instructional data are quickly becoming a focal point for higher education teaching and learning. A small worldwide and interdisciplinary group of scholars held the first Learning Analytics and Knowledge conference in 2011 and published its proceedings. Word about their work and desire for community around LA spread quickly, which inspired many more scholars and LA practitioners across disciplines and roles in higher education to join the discussion and build a community. The Society for Learning Analytics Research (SOLAR) also formalized as an organization and launched the peer-reviewed, open access Journal of Learning Analytics in 2014. SOLAR's aim is to help practitioners in their own institutions and professional roles by sharing everything from R code for data visualizations to case studies of institutional change and faculty development strategies. Private industry has also moved into the LA area as well, with providers of learning management systems (Blackboard, Canvas, etc.), content (Pearson, McGraw-Hill, etc.), and data analytics platforms (Civitas, Loudcloud, IBM Watson, etc.) increasingly contributing to the thought and technology in support of the expansion of LA.

Uses of Analytics in Higher Education

Analytics has been used in higher education for some time to help people synthesize and discern trends in financial information, human resources, enrollment management, and research, with the goals of enhancing course completion and graduation rates. But, institutions of higher education need more effective ways to track and streamline various kinds of data to make teaching and learning more effective, efficient, and engaging. Thus, learning analytics represents a major focus in the effort to gather information, interpret it, and make better decisions.

Using information about students to inform instruction, advising, and academic support is essential to people in a number of roles in higher education. Much of the information acquired in many of those roles has been anecdotal, paper-based and/or historical, which is labor intensive to gather and interpret and, often, available only after an optimal moment to intervene and adjust the learning experience has passed. One benefit of current data collection methods for analytics is that much of the crucial information about the student's experience—from participation in measurable activities designed for their major, to consulting the resources on course sites, and more—is available immediately. Much of it is synthesized and can be provided to advisors, instructors, other support staff, and higher education leaders to identify and respond to issues in timely ways.

One common way of understanding analytics is through distinguishing the kinds of questions that specify the focus and purpose of the inquiry. The accompanying questions below are among the kinds of questions that analytics most frequently answer (for another categorization of data used for analytics, see "data in action, data on action, data for action" in Ferguson et al., 2015):

1. Descriptive: What is happening?

2. Diagnostic: Why did it happen?

3. Predictive: What is likely to happen?

The descriptions that follow include practical examples to illustrate how analytics can answer these questions related to student learning. Note that although the types of questions may each engage in Academic Analytics and Learning Analytics, the examples provide an opportunity to distinguish the focus between the two. The examples provided for the first two categories represent Learning Analytics; the third represents one kind of

Academic Analytics.
(For a discussion that seeks to clarify and align analytics categories, see Barneveld, Arnold, and Campbell, 2012.)

Descriptive Questions: What is happening in my class?

Descriptive questions are in many respects one more tool that instructors can use as they engage in something they do frequently in every course, every term: formative assessment. Instructors conduct formative assessment to determine how well individual students and the class as a whole are learning so that they can adjust instruction to enhance students' learning experiences. Formative assessment can occur in face-to-face and online contexts throughout the term, and traditionally have been carried out by instructors without the use of analytics. For example, formative assessment can be informal and spontaneous (e.g., a face-to-face instructor asking students to write down one or two items from the previous lecture that remain unclear), incorporated into student assignments and scaffolding of skill development (e.g., an online instructor can compare responses to two sets of discussion board posts), and even integrated into an individual instructor's self-reflection on teaching and in revisions to instruction. Asking descriptive questions can be especially helpful for instructors' self-reflection efforts.

Using analytics to answer descriptive questions.

Learning analytics available on an instructor's LMS course site can offer good examples of these kinds of descriptive data. For example, imagine that an instructor has recently revised a course to include more practice activities prior to each quiz. To understand how well students performed on each quiz, a quiz summary can provide the average and range of scores as well as the standard deviation and average time required to complete the quiz. However, suppose the instructor recalls the difficulty students expressed during a recent class discussion about an important concept. Descriptive analytics would offer a way to better understand whether the additional activities that were added to the homework helped students prepare for the quiz or whether another approach is needed to help them learn. Through a quiz summary, the instructor can use question-response visualizations to better understand students' learning. Note that descriptive analytics may inform us about what is happening, but they will not indicate what choice to make in response to the data presented.

Diagnostic Questions: Why did it happen?

Diagnostic questions can play a role in informing both formative and summative assessments in a course. Diagnostic questions, or questions that ask why students perform the way that they do have also been asked by instructors and students long before the use of analytics. For example, one common form of formative assessment that has helped students better understand how their study strategies supported and/or impeded their success on an exam is an "exam autopsy." In this activity, students review a list of exam preparation strategies and then indicate 1) how much time they spent doing each one; 2) what proportion of their overall study time they spent doing each; 3) which strategy was most/least helpful; and 4) how they will allocate their study time for the next exam. This activity has helped students self-reflect on their performance and preparation strategies, and can also allow instructors to guide students toward development in the future.

Using analytics to answer diagnostic questions.

LMSs that include quiz-item analysis features can fulfill a similar function for instructors seeking to learn how well their instructional strategies prepared students to understand and respond appropriately to specific questions. The data available in the LMS is helpful both during the term and afterward by allowing an instructor to track student progress through assignments and assessments as well as to review overall student use of the LMS course site, participation in interactive assignments such as discussion boards or a course wiki, and the extent to which students completed assignments on time.

One challenge of diagnostic learning analytics is that much of the time the data can be quite noisy. For example, instructors may have access to video data that show whether students completed watching a video at all, in one sitting or spread out over time, and whether they re-watched the video, among other data points. However, such data are limited because an instructor will not know whether students also engaged in other distracting behaviors, such as social media engagement, simultaneous to watching the video. Diagnostic analytics offer important data, but those data must be interpreted alongside additional information, perhaps collected from students in other forms, before a complete picture of student behavior is revealed.

Predictive Questions: What is likely to happen?

Advisors have long engaged in efforts to anticipate students' paths to graduation: what foundational skills courses does the student need to be adequately prepared for her proposed major? How frequently is he withdrawing from quantitative skills courses? If she switches to major X next year, how much more course work will she need to complete each term to graduate in four years? Much of the power in the advisor-student relationship lies in the advisor's capacity to consider an individual student's progress data—combined with the information obtained from conversations with that student during advising meetings—in the context of institutional research and college-level student data as well as his/her own experience with other students.

Using analytics to answer predictive questions.

One function of predictive analytics is to provide analyses of data about students' course completion progress and alert the advisor to patterns that may indicate potential challenges. Because patterns of student course progress can be tracked across multiple institutions, educators can now mine multiple thousands of records over many years and to develop models of possible outcomes based on significantly large samples.

The demand to produce and use more data to prioritize investments and initiatives may transform historical expectations about individual institutions' autonomy and prestige. For example, in some areas, institutions have joined together with the educational technology industry to develop and discover new solutions and strategies. As a result of concerted multi-institutional efforts to standardize data and metadata, analytics researchers, educational technology corporations, and consortia of higher education institutions are making strides to leverage these "big data" to identify patterns in teaching and learning effectiveness. Based on these identified patterns, it is then possible to predict which students may fall into academic distress, so-called "early alert" programs, and determine the most likely and effective intervention strategy. Certainly, the data captured about these efforts will also eventually be used to help predict the efficacy of specific interventions for certain kinds of students in specific higher education contexts. This is the potential power of the new learning analytics approaches: the ability to understand and predict when and which students will encounter academic difficulty, provide a personalized intervention, and then measure that intervention's effectiveness to then improve the intervention strategy for future students with similar circumstances. However, since these efforts have involved substantial investment of time and money, further empirical evidence of these interventions' effectiveness would be needed for this to become mainstream.

Up to this point, this discussion has treated LA within the context of Analytics as a whole. To clarify the opportunities and challenges arising from pressure to adopt LA widely in higher education, the rest of the paper will focus on specific LA stakeholders in higher education.

Learning Analytics Stakeholders in Higher Education

Learning analytics can be of value to a variety of stakeholders within an institution. Since pedagogical design and support professionals may vary in their roles within institutions (e.g. they may be faculty members, or may offer administrative leadership at their institutions), the following is a summary of how learning analytics relates to four key stakeholder groups: academic administrators, faculty members, front-line administrators, and students. Since each of the following sections discuss general needs and challenges of each stakeholder group, the following information can be used to understand how learning analytics can benefit professionals in a variety of roles.

Learning Analytics and the Academic Administrator

Academic administrators are often in leadership roles that require decision making for academic institutions, departments, and programs. The traditional way data and metrics have been presented and used in higher education is quickly becoming outdated and insufficient to meet the needs of the modern academic administrator. Although institutions are heavily investing in and expanding their capacity to collect and store data about their learners, and in some cases leveraging those data at the individual course or student level, far less is being done to guide transformation and systemic improvement at a policy level. Regardless of whether they are descriptive, diagnostic, or predictive, learning analytics must:

- provide information pertinent to concerns of academic administrators,
- be clear and simple to interpret, and
- be flexible and responsive to variations in the types of questions that leaders ask.

Rarely do all academic administrators at a single institution want to know exactly the same information. Administrators need tools and analytics that can answer an array of questions while also providing consistent and accurate information. Additionally, the information must be transparent about how and why the data were gathered, how they were analyzed and interpreted; and, for some of the more advanced analytics systems employing artificial intelligence, how recommendations were arrived at.

On a broad level, academic administrators would benefit from using LA to monitor student participation, performance, and engagement as well as to help identify trends or discrepancies in outcomes for students across courses and curricula (IBM, 2016). LA can support academic administrators, who are accountable for the success of all teaching and learning, to do this more easily and flexibly, and to obtain a deeper understanding of their students' educational experiences.

Although there are many powerful opportunities for academic administrators to utilize LA strategically, current LA tools and dashboards frequently offer an abundance of information that, when presented to academic administrators, reads as "noise." More attention is often spent delivering on all the possibilities that emerge from the data rather than focusing primarily on narrowing the data and LA to a few, but powerful, analytics that feed the strategic planning and policy level at the institution. Beyond simply having too much information that has not been curated for the specific leadership audience, additional concerns that frustrate academic administrators when it comes to LA include the following:

When the numbers "do not match."

Academic administrators may have difficulty interpreting data that show multiple disparate answers to a single question. Although some of this cannot be avoided, because there are inherent differences in the ways that some data are defined and gathered based on valid use cases, transparency and simplicity are highly valued by academic administrators. For any audience, it is helpful to explain why there may be a discrepancy when comparing one data set with another, or, alternatively, to provide a single place of reference for questions.

When the data or learning analytics cannot be parsed.

When the data and analytics cannot be disaggregated or "sliced" in a way that is relevant to the college, major, or specific student population, the tool is essentially useless to academic administrators.

When the answer decision makers want is not immediately clear.

Most academic administrators do not have the time to sift through piles of data or charts. They want the answer they are looking for to be at most a few clicks away. The fewer the clicks and the more accurate or clearly explained the data, the better.

When the tool does not work.

This should go without saying, but when academic administrators cannot get what they are looking for because of underlying data infrastructure or design problems, or if the tool is not made to fit their needs, it is extremely frustrating. Oftentimes tools or LA might be designed for a different end user (such as a technology professional), but academic administrators turn to the same tool because there is nothing else that would get them close to their answer. When the functionality they require is either not there or produces confusing results, it will not take long before they stop using that tool or data all together.

When they have to look in a lot of different places to get all the information they want.

Academic administrators tend to be busy juggling multiple responsibilities, which can leave little time, energy, or patience to conduct data cleaning or analysis. The analysis needs to be virtually complete by the time it reaches the academic administrator so their energy can be spent making meaning and asking deeper questions.

Learning Analytics and the Faculty Member

Whereas establishing the technical infrastructure to make data available and developing data models to inform decisions have seen substantial attention, one critical area requiring significant investment is that of faculty adoption of analytical tools to inform educational practice. Unlike educational data mining and academic analytics, or even the student-specific information made available to academic advisors, faculty members must be actively engaged in the process of data-informed decision making in order to fulfill the promise of using LA to improve learning. One promise of LA is that it provides a mechanism for "closing the loop" between teacher and student, for in-class activities as well as out-of-class activities such as homework (Clow, 2012). Nonetheless, it is one thing to acquire accurate data and to understand its implications for instruction; it is quite another to make those pedagogical changes and integrate them into teaching. Clow (2012), among others, is quick to acknowledge, “the key is that action is taken” (p.134).

One substantial difficulty involved in promoting LA adoption among faculty arises from the variety of ways in which faculty structure their courses and use, or avoid using, digital footprint-producing technologies. Such variety then presents challenges to educational technology providers’ ability to standardize visualizations that faculty would find reliable, informative, and actionable. For a “dashboard,” “performance card” or other visualization representing students’ course engagement to be of any use to faculty or advisors, instructors must incorporate into their courses technologies that record the students’ activities. Moreover, instructors must ensure that the technologies are interoperable and that the information resulting from the LA providers’ (often proprietary) analytics does in fact accurately reflect the students’ performance as it is being assessed by the course grading system and other applicable assessments.

As a simple example, an instructor must set up a high proportion of course assignments with due dates in the LMS gradebook by the start of an academic term and promptly grade assignments and post those grades in the gradebook for that instructor and her students to utilize the graphs and analyses that provide a clear indication of student performance and progress. Moreover, this will be especially effective if most of those assignments are submitted online. If, in contrast, an instructor uses few or no assignments—or at least does not use a digital means of receiving the submissions—and/or keeps ongoing grades in, say, a wire-bound vinyl gradebook and only submits grades digitally at the end of the semester, the LA will display information that is neither relevant nor accurate. Insufficient and missing data produce poor analytics.

An especially controversial aspect of LA for faculty is how the data might be used to evaluate teaching or make judgments about employment. Inappropriate use of student ratings of instruction, such as using ratings for summative evaluations without using them for developmental purposes (Benton and Cashin, 2011), or at least the failure of academic administrators to develop consensus with faculty about the evaluation instruments and their use, is already a common “flashpoint” for faculty that stimulates ongoing distrust (see Berk, 2013). Similarly, the urgency for administrators to adopt LA tools and begin showing results from their use may be met with skepticism, if faculty have concerns that administrators will make use of information about courses at faculty expense.

Data stewardship structures, such as policy on who owns what data under certain conditions, can exacerbate this issue. Most LA literature treats data sources from which LA is drawn, such as the LMS, as though they only report on students. In fact, much of what the data points capture is better understood as instructional analytics. The moment a faculty member registers an assignment due date, uploads class materials, or enters a grade in the LMS gradebook, those data points become available to whomever can access them. Already, many universities engaged in “Early Alert” efforts are providing academic advisors (often not faculty themselves) with access to LMS course data during the academic term. The aim is a logical and hopeful one: if an advisor can determine that a student is missing assignments or scoring low on assessments during the first few weeks of the term, she can contact the student and offer resources or create another intervention. The issue with this model is that the reports reveal information about the instructor and course while it is being taught, even as they may reveal little or nothing about the student’s performance.

In this scenario, instructors may or may not be aware that their course data are visible to others, and they may be unaware of who is viewing them, let alone how the data are being used in regard to their students. To be sure, there are now several examples of LA-informed student support initiatives that have garnered campus-wide support (see for example the multiple case studies addressed in Sclater & Mullan, 2016). For better or worse, however, without even looking at student data (such as submission dates, grades, or discussion board posts), one can gather enough information about an instructor's course to draw inferences about the quality of his or her instruction. The timing of when grades are entered, for example, or the number of graded assignments may be misconstrued as representing the sum of an instructor's course design (particularly for online courses), despite the likelihood of their using a variety of very effective methods (and technologies) for instruction and assessment. Unless education leaders engage in deliberate efforts to involve faculty across the institution in discussions and decision-making about LA and how data will be accessed and treated, they run the risk of alienating potential partners in the adoption process, in some cases to the point of faculty resisting even minimal usage of an LMS.

Perhaps the greatest obstacle to effective faculty use of LA is the frequent absence, across academe, of an institution-wide, sustained commitment to this kind of cultural change (Macfadyen, Dawson, Pardo, & Gašević, 2014). LA literature affirms the crucial role that education leadership plays in structuring an appeal, or mandate, in ways that ensure buy-in; encourage skill development; honor innovation and risk-taking; and develop nuanced, faculty-driven expectations for standardization. In one especially poignant piece, Macfadyen and Dawson (2012) draw from change-management literature to account for the challenges of implementing learning analytics. Among other insights, they note that data and logic are insufficient resources for igniting and sustaining change in the diverse and complex university culture. More importantly, they are insufficient for inspiring faculty to make the kinds of deep changes in practice needed to establish and maintain a vital data-informed culture of curriculum development and instruction.

Appealing to the minds of experts must be combined with establishing trust and shared values because

> in order to overcome individual and group resistance to innovation and change, planning processes must create conditions that allow participants to both think and feel positively about change—conditions that appeal to both the heart and the head. Learning analytics has the capacity to do both, but only if certain conditions are met.

(Macfadyen & Dawson, 2014, p. 161).

Ultimately, stories of LA implementation "failures" successfully argue the point that the burden of implementing cultural shifts of university-wide scope belongs to higher education leaders as much as it belongs to faculty. In what may be understood as a confirmation that no one institution is alone in addressing these issues, it is notable that the 2017 Learning Analytics and Knowledge conference featured several presentations and session threads focusing on policy, models of change management, and faculty-driven efforts to explore and broaden the possible uses for LA. Faculty engagement in LA implementation is clearly an area still in need of exploration, discussion, experimentation, and assessment.

Learning Analytics for the Front-line Administrator

While faculty and instructors are critical when it comes to utilizing LA to better understand and support student success, it is often the front-line administrators, such as academic advisors, program coordinators, or other student-success professionals such as success coaches, who need and access LA about a student's entire learning experience. The main challenges for frontline advisors are three-fold. First, the LA that would be most useful for them often requires the integration of several streams of information that often do not speak or play nicely together. A CRM (customer relationship management) may be a key tool to address this challenge, but the implementation, design, and training that accompany that solution are often very labor- and resource-intensive.

Second, if the LA that the front-line administrators could use readily exists, access to the tools and information are often restricted to instructors or other personnel who do not work with the student from a holistic perspective. One thing we must pause and consider when it comes to LA is access and permission levels. Are they serving their intended purpose? Who would really use this information, and use it well, versus who traditionally has had permission to view certain types of course- or student-activity-based information? The siloed and distributed models of collecting and using data inhibit these professionals' ability to work from an accurate and informed perspective. For example, if academic advisors do not have input on what data is collected about students, or do not have access to student data, then they may not receive information that could help them advise their students.

Third, and often overlooked, is the education that is required for front-line administrators to not only use LA tools proficiently, but to also learn how to think with data and ask and answer relevant questions without getting lost in analysis paralysis.

Learning Analytics and the Student

While learning analytics carries a lot of promise, the implementation and use of it is not without its issues. Concerns of privacy and ethics are at the forefront of the learning analytics discussion. These issues primarily center around informed consent, data management, and use of the data (Greller & Drachsler, 2016; Pardo & Siemens, 2014; Slade & Prinsloo, 2013), but additional areas of concern continue to emerge as new LA technologies develop and other LA technologies mature. For example, many institutions are currently wrestling with policies around student awareness of and concern about data use. From a slightly different perspective, institutions must now also nurture student skills in deciphering and making effective use of personal data and visualizations about them. These "student-facing analytics" can be motivating for some students, but there is much concern that they will demotivate others. Advisor and faculty member use of data to enhance motivation could serve to simultaneously reaffirm problems such as stereotype threat, or self-consciousness of an individual's stigmatized status (Brown and Pinel, 2003; Dweck, 1999). For example, a student of color may worry that data collected about them may conform to or reaffirm negative stereotypes about people of color in general. Lastly, there is the question of how students should own or use data about themselves, which depends on what data they have access to.

It is not currently clear how aware students are of how their personal data is used within the institution. Although there are laws and policies in place in the United States (e.g., Institutional Review Boards [IRB] and the Family Educational Rights and Privacy Act [FERPA]) to address how data are used outside of the institution, there is not the same oversight within the institution (Pardo & Siemens, 2014; Slade & Prinsloo, 2013). Furthermore, whereas students are more and more aware of how their personal data are used in social media and internet commerce, how much that awareness translates to their educational institution is unknown (Slade & Prinsloo, 2013). The discussion about how students can provide informed consent, and whether they need to is, consequently, still in its infancy (Siemens, 2013). Moreover, learning analytics bring a level of complexity to privacy laws because of the multiple systems across institutions, as well as with partner vendors, that hold student data. Even when institutions have centralized data storage, the question of informed consent is still unclear. Although some systems allow students to keep their data confidential in some circumstances, how that confidentiality works in practice (e.g., advising) has not been addressed (Greller & Draschler, 2016).

Who “owns” student data and how those data are used are ethical issues that need to be addressed within higher education. Indeed, irresponsible use of data may result in students being categorized in ways that may or may not be predictive of their futures (Slade & Prinsloo, 2013; Pariser, 2011). Higher education can be a time when students are able to start anew, when they can redefine who they are, and who they will become. Although pattern recognition can be powerful in helping to guide students (Wagner & Ice, 2012), it can also be a way to keep students stuck in the very place they came to higher education to leave behind. For example, a student may have shown a certain pattern of behavior during high school, such as poor attendance or low grades, but they may be motivated to “start over” once they are in college. However, if learning analytics tools show patterns of students’ past behavior to their instructors, these students may not experience the fresh start they desire.

We also cannot know everything that a student does. LA is only able to make predictions on quantifiable behaviors and is not able to take into account what happens when the student is not interacting with an LMS or other data collection mechanism (e.g., card swipes). Furthermore, LA does not cover the quality of student interaction with academic life, such as course material. The range of data sources (e.g., vendor, faculty-generated, self-reported) also can result in a variety of data uses that are inconsistent across courses and the diverse interfaces of university applications. Finally, there is work still to be done regarding how to design, report, and act on data in ways that are equitable or that, at the very least, are not disproportionately affecting students from different cultural, demographic, and educational contexts.

One area worth exploring is the students’ roles as producers and consumers of their own data. The predominant discussion assumes that they--and the data they generate--are passive objects of study (and of pedagogical choices, more broadly). Engaging students in research partnerships about their data is one possibility that could both enhance students’ data literacy skills and offer them an independent role in educational data interpretation.

Data Literacy Professional Development

As the expectation to use data broadens across college and university administrative and academic units, higher education has begun to address the need to develop data literacy and maturity across campus communities. This can ensure that various stakeholder groups have the training they need to use data appropriately and purposefully. The following is a discussion of what data literacy training different stakeholder groups need in order to use learning analytics.

Administrators

Two main groups of academic administrators require very different types of professional support and levels of data literacy based on the reason they might use LA and how they in turn make decisions or actions based on the information. Unit leadership, such as directors, department heads, and associate deans, may require more contextual knowledge and a richer understanding of the nuances in the data, i.e., what are available, what the definitions mean, and what is possible. For example, a department head may want to understand differences in a course outcome following instructor feedback and consultation, or differences in student outcomes by previous coursework. They may want a deep understanding of how learning analytics can help them answer these questions and make decisions, as these leaders are partners in the development and creation of the tools and information that will be most informative and actionable. Their role dictates they "know the data" so that they can be responsive to their units and set direction but also be responsive to the executive leadership in terms of meeting milestone and high-level goals. In contrast, senior leadership, such as the deans, provost, president, and other executive leadership largely need a short list of information that they monitor and can use easily. Although information about methodology or contextual information about the tool can be useful, there is a greater need for ensuring that the "tool works" and that administrators can say with confidence what the results say/indicate.

Faculty

LA represents an approach to working with learner data that enhances formative as well as summative assessment, so it is critical that curriculum, instruction, and related data collection are centered on the skills and knowledge a course claims to address (Kandiko & Blackmore, 2012; Suskie, 2009; Chickering & Ehrmann, 1996; Angelo & Cross, 1993). Assessment and LA also share the same fundamental weakness: the quality of the decision or action to be taken based on the information revealed by LA/assessment depends on the degree of alignment between what is taught and what is measured (and, hence, what data are collected).

Adopting LA effectively requires that faculty members not only adjust how they previously ran their courses, but also, frequently, confront deep convictions about teaching and learning as well as concrete limitations such as time and resources. Scholarship in a variety of fields, including education, has articulated the difficulties in creating and sustaining changes in practice (e.g. Lim, Wang, & Graham, 2019). But instructors who are trying a new teaching strategy, particularly one involving a new mode of assessment, will attest to the time, effort, and risk associated with that effort. Moreover, the ability to revise instruction, course activities, and student feedback, in response to learning analytics can take a great amount of skill. The skill to continuously evaluate and revise various aspects of teaching may be something that faculty will need to continually develop throughout their careers.

Front-line Administrators

There are at least two important groups of front-line administrators that need training in data literacy: those that work with faculty and those that work with students.

Faculty-facing administrators

In addition to the burgeoning international, interdisciplinary efforts in LA to genuinely learn more about how/where/when learning happens, and to equip faculty with usable information to improve teaching, there is equal commitment to educational development for faculty. Although LA adoption represents a significant change in faculty roles, successful educational development organizations have shown resilience and ingenuity in their capacity to anticipate the skills for those roles and to equip faculty to achieve them (Sorcinelli et al., 2006). Related efforts, particularly those involved in supporting faculty incorporation of evidence-based instructional practices into their courses, have demonstrated the potential for enhanced learning outcomes and increased faculty engagement by enlisting educational developers in cultural transformation efforts about teaching and learning (cultural transformation efforts include incentives, reflection, mentorship, and collaboration as described in Stieha, Shadle, & Paterson, 2016).

Helping faculty integrate LA into their overall assessment and instructional practice and guiding institutional conversations about the ethics of its use represent significant, complex, but worthy opportunities for educational development units, whether they focus on face-to-face or online learning (or both). The opportunity extends to roles beyond the typical confines of educational development, as well. Promoting adoption of LA will require broadening faculty skill sets to include data analysis and data literacy. Doing so will also expand their technology literacy regarding selecting technologies to support their teaching: any specific visualization, set of metrics, or integration of these into a course/learning environment must be well-suited to their course learning goals and program learning outcomes (Bouwma-Gearhart & Collins, 2015; Kozma in Ehrmann, 1995, p. 6).

Student-facing administrators

Student-facing administrators experience some similar challenges to faculty-facing administrators, such as gaining access to data and creating systems to enrich their efforts in addressing student support. These challenges extend in multiple directions, revolving around:

- the means to assess the needs of diverse students;
- understanding and responding to student data awareness and literacy;
- assessing the effectiveness of tools, systems, and human resources deployed to respond to those needs;
- and, finally, the need to develop and maintain an iterative process of continuous improvement to meet the changing needs and demands of the student populations.

Compounding these challenges are several other factors. The student-facing administrator works increasingly in an environment where budgets are shrinking and demands are increasing for administrators to enhance the ‘personalization’ of student support to ostensibly improve student persistence to graduation. In addition, administrators also need to choose which technologies to use for data informed decision making. All of this implies the need for the student-facing administrator to have strong technical awareness and data intelligence.

In contrast to those challenges is the huge potential for student-facing administrators to illuminate and enhance the student’s educational experience by using data combined with human resources to understand the student more holistically. Combining data and analytics with other skillsets could help student-facing administrators surround and contribute to the student’s ability to effectively engage in academic pursuits. As institutions consider and develop methods of using data to improve upon the academic engagement and achievement models, student-facing administrators must effectively join with their academic partners to integrate systems for seamless and accessible student support. A unified, data-informed, holistic approach to understanding the student’s entire experience, inside and outside of the classroom, is now more possible that ever, which will then allow for clearer information sharing to improve the educational enterprise as a whole.

Students

Given that a student’s academic achievement is dependent, to varying degrees, upon multiple institutional support systems, a major challenge is informing students in the most immediate, easily accessible and useful form. Navigating an institution’s voluminous set of policy, process, and support resources is daunting for most students. Couple this with the challenge of providing students with timely and actionable information on their academic performance and sources for support, and it is not surprising that many students simply do not know where to turn when they experience academic distress. While institutions attempt to address these information challenges, an equal problem is the student's ability to effectively make sense of and act upon the information that is provided. As with so many aspects of the student's experience, learning to navigate educational institutions and the academic enterprise is a learning experience in itself. There are several sets of skills students must be taught and acquired in order to take the fullest advantage of the breadth of support and information services available at their institutions, while maintaining the integrity of their educational experience. Two important sets of skill acquisition are understandings of "information literacy" and "data literacy" and what they mean within their academic career and beyond.

A useful articulation of the concept of information literacy has been advanced through the Association of College and Research Libraries, and its development of a Framework for Information Literacy for Higher Education: "Information literacy is the set of integrated abilities encompassing the reflective discovery of information, the understanding of how information is produced and valued, and the use of information in creating new knowledge and participating ethically in communities of learning" (np, 2016). The implication for institutions is the need to ensure that the ease of access to information is balanced with educating students on the appropriate and ethical use of information gleaned from widely available digital sources, as well as the ability to differentiate reliable and valid sources of information.

Similar to the issues described earlier regarding data literacy as it relates to institutional administrators and leaders, the same issues of appropriate use, reliability, access, and validation apply to student data literacy. In the same way that information literacy can affect the quality and integrity of educational outcomes, a lack of understanding of what data are, and how data are gathered, analyzed and interpreted, can affect the outcomes of the student's efforts.

This distinction and interconnectedness of the concepts of data and information literacy has direct implications for the use of student-facing learning analytics systems. The information that is provided to students via systems that gather and interpret student performance data to then 'inform' students of their progress is only as valuable as the student's understanding of the information. Furthermore, and perhaps more importantly, the student must have an understanding of the implications of that information; in other words, what actions should the student take?

Concluding Thoughts

The current race to make greater use of the voluminous amounts of data that are available to inform the teaching and learning experience presents a new challenge and responsibility for faculty, administrators, and support staff. As new technologies become available at an ever-increasing rate, giving the academic community more access to data, the ethical decisions in what information to share with students and how, becomes even greater. For example, artificial intelligence machine learning analytics can produce insights by processing extremely large, complex and varied data sets; however, the caveat is that it is difficult to ascertain how these analytic systems arrive at those insights. This is not to disparage the promise of such efforts, but instead to remind educators to consider analytics processes, output of data analytic efforts, and more importantly, the ethical and appropriate use of the resulting "information."

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