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Learning Analytics: Translating Data into "Just-in-Time" Interventions

Pauline Salim Muljana
Old Dominion University, Virginia, pauline.muljana@gmail.com

Greg Placencia
California State Polytechnic University, Pomona, gvplacencia@cpp.edu

LEARNING ANALYTICS: TRANSLATING DATA INTO "JUST-IN-TIME" INTERVENTIONS

Pauline Salim Muljana[1], Greg Placencia[2]

[1]Department of STEM Education and Professional Studies: Instructional Design and Technology, Old Dominion University, Norfolk, VA
[2]Department of Industrial and Manufacturing Engineering, California State Polytechnic University, Pomona, CA

Abstract

Despite the burgeoning studies on student attrition and retention, many institutions continue to deal with related issues, including D, F, and W grades rates. The emerging and rapidly developing Learning Analytics (LA) field shows great potential for improving learning outcomes by monitoring and analyzing student performance to allow instructors to recommend specific interventions based on key performance indicators. Unfortunately, the important role of LA has not been fully recognized, and therefore higher education has been slow to implement it. We, therefore, provide the rationale and benefits of increased LA integration into courses and curriculum. We further identify and suggest ready-to-implement best practices, as well as tools available in Learning Management Systems (LMSs) and other helpful resources.

Keywords: student retention, student attrition, learning analytics, course design, instructional strategy, learning management system, DFW rates

Introduction

Institutions have battled with student attrition and graduation rates in higher education (such as in two-year and four-year institutions), despite several decades of research (Appana, 2008; Berge & Huang, 2004; Tinto, 1982). Unfortunately, institutions working to reduce attrition rates may encounter rigid constraints like inadequate budgets, misperception of academic quality, and reduced course registration (Liu, Gomez, & Yen, 2009; Poellhuber, Chomienne, & Karsenti, 2008; Willging & Johnson, 2009). Using existing or easy-to-obtain indicators is now a viable option. For example, decreasing the number of students receiving D, F, or W grades—DFW rates—at the course level has shown to be effective at reducing attrition (Hudson et al., 2014; Urtel, 2008). Monitoring students who display early "at-risk" signs—especially for D, F, or W grades—has also been found to improve performance effectively (McGuire & McGuire, 2015).

Improved technology can help instructors utilize data to find meaningful learning patterns and anticipate behavior regardless of whether the instruction is remote, hybrid, or traditional face-to-face. For example, businesses scrutinize customers' behavior and characteristics using data analytics to predict future product success (Dietz et al., 2018; Finger & Dutta, 2014; Fritz, 2011; Macfadyen & Dawson, 2010; Sclater, 2017). In addition, analytics-related practices in business, referred to as business intelligence, are conducted in the background to gain a better understanding about people's activities (also called consumers' behaviors), according to Sclater (2017). Business organizations use such insights to optimize their processes and outputs (Sclater, 2017) to support people's activities and meet consumers' needs. Moreover, businesses utilize data analytics to find a connection between individuals' past activities, underlying mindset, and most likely future activities using a series of generalized techniques to uncover correlations among hidden variables, relationships, and trends, regardless of domain. Therefore, while business and higher education differ in nature, the basic tools upon which learning analytics is based have a proven record of accomplishment upon which higher education can build. In addition, both institutions "are influenced by money," according to Dr. Mark Glynn, as quoted by Sclater (2017, p. 28). They are committed to helping students succeed and thus many institutions actively find ways to increase the graduation rate. Some efforts entail "things like taking care of the students throughout the institution, their transition during the first year, how they integrate into the social environment of the university. These are the types of things learning analytics can also detect," said Dr. Abelardo Pardo as cited by Sclater (2017, p. 29).

Adopting learning analytics (LA) may seem convoluted, but academia stands to benefit greatly from similar analysis through the field of LA, which is implementable with relatively little additional investment. For instance, most universities and colleges already use Learning Management Systems (LMSs) to deliver course content to students. LMSs often provide detailed data logs that can be mined for actionable insights into current learning processes and to find behavioral patterns in learning outcomes so that instructors can improve learning performance (Dietz et al., 2018). Moreover, at the course level, LA is believed to have the capacity to help instructors detect struggling students early on by monitoring their progress and intervening at critical points according to the student's needs, resulting in lower attrition rates over time (Casey & Azcona, 2017; Dietz-Uhler & Hurn, 2013; Strang, 2016). Although scholars have explored this topic by using LMS logs to determine interventions for improving learning outcomes, LA research and practices are still in the early stages, particularly in academic settings (Dunbar, Dingel, & Prat-Resina, 2014; Firat, 2016; Greller & Drachsler, 2012; Siemens, 2013; Verbert, Manouselis, Drachsler, & Duval, 2012). We maintain that academic stakeholders like administrators, faculty members (also referred to as instructors), and instructional designers can better serve student needs by better utilizing LA.

We believe, as did Kilgore (2016), that instructors should focus on learners' needs first by decoding their behavioral learning patterns. While technological development such as LMSs create a paradigm shift at all levels of education, they also necessitate adaptation of good Learner Experience (LX) design and instructional strategies to fulfill varied student needs. Therefore, we will outline how educators and instructional designers can use LMS tools to assess student interaction with learning materials more precisely and develop course structures that encourage better student engagement. Kilgore (2016) has affirmed that educators and course designers can "make more and better-informed choices on content delivery to help students better understand the critical concept." Used properly, LAs can help instructors dynamically adjust course elements and instructions to improve individual and collective student performance by aligning current learning progress to meet student learning needs more effectively.

This article discusses analytic types in higher education, how LMSs increase the need to adopt LA, the benefits of LA integration into teaching and learning practices, best practices for implementing LA throughout a course term, available LMS tools, and several useful resources. We intend to encourage instructors to consider implementing LA techniques and conduct their own studies to contribute to the emerging LA field. Likewise, we invite instructional designers to perform data-informed, user-need analysis prior to designing and developing courses for enhancing student learning experiences.

Analytics in Higher Education

Before reviewing the definition of LA, identifying the types of analytics provides insight into LA's role in higher education. Barneveld, Arnold, and Campbell (2012) have suggested the following analytics types for use in higher education settings as well as a definition of each:

1. Analytics is an umbrella term for whenever data is used for decision making at all levels.
2. Academic analytics refers to institutional–level processes to obtain and utilize data for operational and financial decision making.
3. Learning analytics is an analytic technique used to improve learning outcomes at the

departmental or course level, which is the focus of this article. Perceptions of scholars and practitioners in academia, together with the findings of scholarly studies, are further presented in the later section of this article.

4. Predictive analytics is defined as statistical analysis that can be used at all levels to obtain information to investigate relationships and patterns for anticipating behaviors and critical events. An example model of open learning analytics architecture in higher education (Sclater & Mullan, 2017), viewed from the predictive lens, is illustrated in the Appendix section.

While each analytic type has its own traits and is performable at different levels, they all share the ultimate goal of improving student success while lowering attrition rates over time.

At a macro scale (Ifenthaler & Widanapathirana, 2014), beyond course-level analytics, the analytics techniques called academic analytics and predictive analytics can be performed to assess the areas that most need improvements. For instance, studies show that institutional support and services to students yield a positive impact to student retention (Gaytan, 2015; Heyman, 2010; Nichols, 2010; Shaw, Burrus, & Ferguson, 2016). Both academic and predictive analytics serve an imperative role in facilitating decision-making in establishing suitable support and resources that are focused on those in need. As early as possible, data can be retrieved and analyzed (Raju & Schumacker, 2015; Torres, And, & Eberle, 2010) to identify which students have withdrawn from a course or have enrolled in courses with high incomplete rates. These students are not likely to persist through the learning process, nor be retained in the program (Cochran, Campbell, Baker, & Leeds, 2014; Wladis & Hachey, 2017; Wladis, Hachey, & Conway, 2014). Receiving such actionable insights, administrators may work with other stakeholders (faculty and staff members) in developing and launching improved procedures or programs such as professional development opportunities—like course redesign program—crafted specifically for instructors of disciplines with high incomplete rates and orientation modules covering effective learning strategies appropriate for students of these disciplines (Muljana & Luo, 2018).

For the purposes of this paper we adopt the most cited definition for "analytics at another level," referred to as LA, as established by the prominent learning analytics organization, the Society for Learning Analytics Research (SoLAR). SoLAR defined LA as "the measurement, collection, analysis, and reporting of data about learners and their contexts, for the purpose of understanding and optimizing learning and the environment in which it occurs" (Siemens & Long, 2011, p. 32) at the First International Conference on Learning Analytics and Knowledge in 2011 (Ferguson, 2012; Strang, 2016).

The society's definition highlights two key elements. First, it proposes measuring learners and learning outcomes within a specific context. Second, analyzing data and reporting the findings are conducive to improving learning and the learning environment. For example, at the program level, course completion data reveals the most challenging courses, gateway courses, and courses that help students to exit the program. Analyzing these data can engender patterns to inform decisions on improvements, such as a program adjustment, possibly by changing the order of the courses to help students transition through courses in accordance with the pre-requisites and difficulty level (Dietz, Hurn, Mays, & Woods, 2018). At the course level, LMS course usage data are useful in determining necessary course elements for enhancement and serve as guidance for designing or redesigning courses (Dietz et al., 2018). Put simply, LA highlights the role of confirming "gut instinct" at detecting at-risk students and establishing appropriate remediation by using data analysis to increase its accuracy (Dietz-Uhler & Hurn, 2013). We further infer that LA does not replace any learning theory; rather, it helps instructors triangulate and comprehend learning and its environment prior to making decisions on improvements. After all, data analysis is only as good as its coherence with relevant pedagogical goals (Gašević, Dawson, & Siemens, 2015).

Ubiquitous Adoption of LMS

The prevalence of LMS has influenced the adoption of LA in higher education. A 2013 national survey found that 99% of 800 institutions within the U.S. had adopted LMS (Dahlstrom, Brooks, & Bichsel, 2014) and that most of their faculty admitted using LMS and highly regarded its features to enhance teaching and learning. This indicates a paradigm shift beyond LMS's early role as a content repository and delivery portal.

LMS records learning activities and participation, making tracing student activities and monitoring their progress more feasible (Martin & Whitmer, 2016; You, 2016). Moreover, it affords a capability to detect struggling students early within a course term (Macfadyen & Dawson, 2010) by analyzing readily available data that LMS programs store by default (Casey & Azcona, 2017; Valsamidis, Kontogiannis, Kazanidis, Theodosiou, & Karakos, 2012). Examples of available LMS data (Dietz-Uhler & Hurn, 2013; Dietz, Hurn, Mays, & Woods, 2018) include: (a) number of times a resource is accessed; (b) data and time of access; (c) number of discussion posts generated; (d) number and date/time of messages to the instructor; (e) assignment submission timestamp; (f) types of resources accessed; and (g) grades on discussion forum, assignment, test and final grades. Dyckhoff, Sielke, Bultman, Chatti, and Schroeder (2012) additionally suggested a way to use analytics as a checkpoint to promote preparatory learning activity. Student login and access behaviors are observable within an LMS course to indicate if students have or have not initiated a learning sequence. Such data can direct instructors to prompt, remind, or encourage students to start the learning process.

Additionally, instructors can gather qualitative data by using tools like discussion post themes and reviewing questions asked during instruction and contributions within collaborative projects. These can indicate student engagement, student retention, and knowledge acquisition. Collecting these indicators is also useful for instructors in monitoring current learning progress and student engagement, identifying struggling students, and determining necessary interventions to boost student outcomes (Casey & Azcona, 2017; Dietz-Uhler & Hurn, 2013; Macfadyen & Dawson, 2010). The aforementioned suggestions are additionally beneficial in informing course content adjustments (Dyckhoff et al., 2012).

Our reactive reflection on this LMS proliferation is that the data capturing learning behaviors are readily available at the instructors' fingertips. Put simply, collecting these LMS data is considered non-intrusive and does not entail advanced interference from faculty or staff members (Macfadyen & Dawson, 2010). Our intent is to encourage the use of LMS usage data to inform intervention decisions—congruent with of any kind of learning theories held and learning objectives to achieve—intended to help students perform better.

Benefits of Learning Analytics

In better understanding the benefits of LA in higher education, we discuss scholars' and practitioners' perceptions and the substantive evidence from the existing research on the influence of LA tactics toward the enhancement of learning outcomes.

What the scholars and practitioners perceive

Sclater (2017) investigated the perceptions of scholars and working professionals in higher education to determine their motivations for studying and adopting LA. Most indicated LA's vast potential to improve education as a primary driver. We briefly examine their collective responses and provide highlighted quotes, annotated with support from scholarly research.

Understanding the learning process. A critical element of LMS is the ability to perform non-intrusive, real-time data gathering and analysis. Such an approach bolsters intuitions instructors often have about student performance, which allows instructors to determine more accurately when students succeed, struggle and improve, or, most critically, struggle and fail to improve (Johnson, 2017). LA provides a capability to assist educators in understanding "learning as a dynamic process rather than a series of snapshots … we can be much closer to the decisions that learners are making, and based on that we can have a much more complete picture about learning," said Dr. Dragan Gašević as quoted by Sclater (2017, p. 21). More importantly, instructors can trace students' digital footprints to pinpoint critical learning points, accelerate successes, and remove roadblocks. Another advantage of LMS is that because students' records are readily available and retrievable, instructors can conduct long-term observations to reinforce decision-making about course content and adjust instructional strategy as needed.

Enhancing learning. As instructors understand student learning processes better, instructors may reflect on the efficacy of current instructional strategies and resources and remove those identified as ineffective. For example, we juxtapose the concept of learning processes with signal-to-noise ratio (Kim, Glassman, Bartholomew, & Hur, 2013; Sun, Xie, & Anderman, 2018). We define signal-to-noise ratio in learning as the amount of content required to achieve subject matter proficiency compared to the amount of residual elements, e.g. non-essential, extraneous course materials and course structure. A course with a good balance of signal-to-noise ratio is transparent and has easy-to-navigate expectations that result in an accurate and timely assessment. As Dr. Stephanie Teasley, the President of SoLAR, professed in Sclater's book (2017, p. 22), "[I've] been doing research on learning for a long time and [I] have always been very interested in doing very close analysis of behavior to understand what aspects of the learning experience are most closely tied to cognitive gains." Thus, an LA approach is predominantly evidence-based, which allows instructors to recognize when learning processes result in true cognitive gains to know when course changes enable these gains and most importantly how to transmit content more optimally. As a result, both instructors and students can evaluate their own improvement process in real time (Ifenthaler, 2017; Ifenthaler & Widanapathirana, 2014).

Leveraging the use of empirical data. LMSs continue to be used primarily for information/content delivery and outside-class interaction (Dahlstrom et al., 2014). This indicates that despite popular adoption, their advanced, built-in features for analytics and improving learning performance remain underutilized (Dahlstrom et al., 2014). LA scholars and practitioners have encouraged using these analytical features to identify underlying patterns that can explain behaviors and learning strategies associated with superior performance (Firat, 2016; Goda et al., 2015; Yamada et al., 2016, 2017; You, 2016). Additionally, examining data and recognizing patterns are helpful to instructors in formulating new questions and hypotheses aligned with learning theory and related to learning context. This idea is reinforced by Dr. Alyssa Wise, in Sclater's book (2017, p. 24):

> The real drive is turning all this abundant data that is being generated and could be generated into useful, actionable insight…There's a nice relationship between when data becomes available, and realizing new questions you can ask — so I don't think it's just about using data to answer the questions you already have, but also for question generation.

Personalizing instructions. Students enter classes with differing prior expertise and experience, which affects the learning pace. Since LA can detect underlying patterns, it promises to match course pace and content to students' learning processes (Daniel, 2015) through personalized scaffolds and environments (Elias, 2011; Ifenthaler & Widanapathirana, 2014; Kim et al., 2016). Although one size does not fit all, the potential for "mass customization" tailors commonalities to accommodate diverse learning needs by introducing fundamental knowledge as needed. For example, students with limited prerequisite knowledge can receive deficit-focused instruction, while students with learning disabilities can receive special instruction. Another example described by Dr. Mark Milliron, in Sclater (2017, p. 25), is:

> My own theory is that second, third, fourth generation students are scaffolded by the stories of the people who came before. If they get stuck, someone can come and help them. We now have a lot of first generation students who don't have the same kind of social networks. Learning analytics at their best, and I'm broadly defining learning analytics, can help that student understand the next set of choices they can make. We can help scaffold the student at that stage—part of the scaffolding by the way is to engage them when it's time to get tougher— it's not about spoon-feeding them— it's about getting them the right resources at the right moment and helping them in a way that most students in second, third, fourth generation are being scaffolded anyway.

Intersecting multiple fields. Learning issues are complex, which favors a multidisciplinary approach to providing solutions. As expressed by Dr. Abelardo Pardo (Sclater, 2017), one unique advantage of LA is that it integrates diverse fields, including psychology, educational psychology, pedagogical theory, data analytics, and technology constructs. Data lacks meaning when unaligned to pedagogical theory and learning context (Gašević et al., 2015). Understanding pedagogical intent and how multiple disciplines expound the data's context plays an important role in analyzing students' learning behavior in different learning conditions (Gašević, Dawson, Rogers, & Gasevic, 2016). Properly implemented, LA requires a symbiotic relationship among multiple fields such that they align their key attributes to support the ultimate goal of improving education.

What the research studies have revealed

Student persistence during the learning journey is associated with academic completion (Eliasquevici, Seruffo, & Resque, 2017) as well as with course achievement. Such persistence is influenced by underlying behavioral characteristics possessed by the individual students. A couple examples of these behaviors are self-regulation (O'Neill & Sai, 2014) and metacognition (Lee, Choi, & Kim, 2013). Since these characteristics are latent variables (non-directly observable nor measurable), assessing and fostering these behaviors can be challenging. However, it is now more feasible through the utilization of technology to offer analytics features (Roll & Winne, 2015), since these tools are capable of tracing learning behaviors. A small, but growing, number of studies have examined these characteristics in triangulation with other measurement techniques, like LA. We present the following studies that utilized self-report measurements and course usage data.

In these two studies, data related to assignment completion rates (Goda et al., 2015), the access frequency to the materials, and regularity of study time were collected and classified into different types of learning patterns before making a correlation with course achievement (You, 2016).

Enhancing learning outcomes, the findings signify the importance of promoting learning behaviors associated with theoretical constructs of self-regulation such as scheduling study time sufficiently, submitting assignments on time, accessing course materials regularly, and reviewing course instructions or materials frequently in LMS. Thus, the researchers have recommended the analysis of course usage data early in the course term in order to catch potential at-risk students and deploy suitable interventions to meet these students' needs in time.

In a longitudinal study, Tabuenca, Kalz, Drachsler, and Specht (2015) revealed that having online students log and monitor their study time scaffolds their time management skills (which is a crucial factor influencing one's self-regulation), particularly when encouraged at the beginning of the course term. In addition, the course usage log displayed high activities immediately after delivering a notification or course announcement. Notifications comprising tips on learning strategies were also found to have the most effect on students' time management and study planning. The timing of delivering notifications or announcements (sent at scheduled times versus at random times) had a moderate impact on time management skills as well—scheduled notifications were discovered to be more effective. Their findings have suggested that employing consistent course notifications or announcements containing meaningful updates and reminders foster positive learning behaviors. Like Dr. Mark Milliron, we reiterate that this is not spoon-feeding the students, rather we proactively provide them with the appropriate resources at the right time before it is too late to help them (Sclater, 2017).

A study published in 2016 examined 151 modules used by more than 111,000 online students from various disciplines to predict academic retention (Rienties & Toetenel, 2016). Using a learning analytics technique, the researchers discovered that course logs (time spent on the course site) were positively linked to the social learning activities or communication activities in class that had been found to predict academic retention, which researchers operationally defined as students who received a grade of C or better. Hence, designing socially engaging learning activities that align with course learning objectives is one heuristic practice for enhancing academic retention. Through LA methodology, this study has implications for extending research on pedagogical theory related to social learning that can influence academic retention in a profoundly positively way.

Although primarily utilizing LMS course usage data, the following study also offers salient findings. Comparing two courses, one using adaptive released modules and the other in a controlled environment without using an adaptive release function, researchers discovered that timed adaptive release modules motivated students to spend more time per session (Martin & Whitmer, 2016). The difference between both groups was reportedly significant. The study essentially inferred that students in the experimental group were likely to engage better with the learning materials because their access to the course modules was more focused. From this finding, we learn that releasing a special module (such as remedial resources or learning materials) to those who need it may increase the exposure to the course topics, with which they have been struggling. Further, it implies that a course-content adjustment performed according to evidence-based behaviors, such as the frequency of course access and time spent on the materials, has an impact on student-to-content engagement.

The current state of LA recommends itself highly as a tool to improve student performance in higher education. The success of data analytics, from which LA is derived, offers great benefits to improve student success by assisting instructor efforts and potentially decreasing workload. While it is tempting to consider successes in the business domain to be mutually exclusive to those that could be achieved in the learning domain, the generalized nature of data analytics at identifying correlations between past activities, current mental perceptions, and future activities makes adoption of LA compelling. With this in mind, we present suggestions to "jumpstart" instructors in higher education who are considering adopting LA.

Best Practices

Given the aforementioned rationale and benefits of LA, we recommend a set of ready-to-implement best practices to assist instructors seeking to adopt an LA approach using LMS. These can be applied throughout a course term within the web-assisted, hybrid, or online environment. Although these recommendations may sound simple, designing effective courses may be challenging. Fortunately, many institutions provide supporting personnel such as instructional designers, whose services we highly recommend. Moreover, good course design should entail an iterative process, not a single implementation.

Before the course term starts

Positive learning experiences start with effective course design. Therefore, preparation prior to the course term is essential to ensure successful teaching and learning processes (Feldman, 1996). Instead of immediately uploading course materials to the LMS, instructors may want to consider deploying consistent and logical course structure. Clarity and consistency of course layout are positively associated with students' perceived learning (Swan et al., 2000). One approach is to develop weekly modules and incorporate materials and assessments accordingly and chronologically. Such course development would result in easy navigation and assist students in establishing learning routines. Moreover, a well-planned course layout motivates a learning atmosphere. Students frustrated with course navigation may feel discouraged and demotivated to further explore the content (Simunich, Robins, & Kelly, 2015).

Another critical element is to give a set of clear and measurable learning goals or objectives (Swan et al., 2000) at the beginning of each course module to orient students' efforts. Learning objectives appear to increase course transparency by communicating to students what an instructor expects them to achieve by completing the module, which potentially increases their competence (McGuire & McGuire, 2015). Such objectives further allow students to gauge their own level of competency and recognize whether it matches class prerequisites and those of later courses. These objectives form the basis of curriculum criteria and key performance indicators that appraise students' achievement over time.

We also recommend creating a course calendar within the LMS during the design phase. The calendar functions like a course schedule/timeline that enables instructors to organize the course and provide a clear timeline for student deliverables. Course calendars add further value by providing reminders to instructors and students, as well as the ability to deploy course material, schedule assignments, and other deliverables automatically.

It is undeniable that students have diverse learning needs (Lewis & Sullivan, 2018) and enter classes with varying levels of prior expertise and experience. One strategy to diagnose current levels is by conducting a pre-assessment before course instruction begins. It can be as simple as asking students about their level of comfort with the technology (Woodley, Hernandez, Parra, & Negash, 2017), the pre-requisite theoretical foundation, and their motivation(s) for taking the course. Administering anonymous quizzes and/or discussion boards through an LMS helps instructors conduct such assessments (Woodley et al., 2017).

At the beginning of the course term

It is imperative to set the right tone for students (McGuire & McGuire, 2015) at the beginning of the course term to convey clear expectations. The first interaction with students, like a welcome message, should emphasize the importance of frequent download and review of course materials, and the expectation that students should employ regular study time. Students who frequently access course materials often perform better (Zimmerman, 2012). We, therefore, recommend a course tour on the first day to reveal the "big picture" of what the course entails and to allow students to understand the course structure and location of materials and assessments. If the agenda of the first-day class is full, a short video is suitable to deliver a virtual tour.

Moreover, LMSs have statistical features allowing instructors to observe when, and often where, students last accessed the course site, although these tools have different labels within different systems. Since scaffolding can teach learning strategy (Zimmerman, 2002), students who do not access a course for a long time can receive email reminders regarding the importance of regular access to course materials. Most LMSs allow instructors to email students directly from the course site with a few clicks, either individually or collectively. In addition, analyzing course access statistics reveals patterns about when (day and time) students most commonly access the course to guide when course update should occur so as to reduce the likelihood students will miss them. Automated announcements linked to updates or deployments of course material or assessments provide another option.

During course term

As course instruction progresses, instructors may establish an iterative process, repeating actions as necessary. As students engage in learning activities and complete assignments or assessment, it is necessary to monitor their progress as early as possible. We highly recommend analyzing course usage data early in the course term to anticipate course achievement, identify learning problems, and decide whether to employ just-in-time interventions to improve student performance (You, 2016). In cases where students miss or submit late assignments and/or receive poor scores, instructors can offer support like motivational feedback or studying tips. When students are passive in online discussions, similar interventions can be executed. To reiterate, many LMSs provide email features without necessitating extraneous steps.

Monitoring formative assessments is helpful in tracking the learning progress. We define formative assessment as an evaluation method performed while learning is still occurring that provides information needed to move learning forward (Heritage, 2007). Quizzes and tests are common formative assessments that LMSs, like Blackboard, allows instructors to determine the validity and reliability. Such analysis results potentially reveal the most difficult test item and hard-to-grasp topics. As a result, instructors can use empirical data to assess the efficacy of materials and/or interventions. In essence, improvements such as revising instructional strategies, updating learning activities and assignments, and releasing remedial materials may occur iteratively throughout the term.

At the end of the course term

Instructors often evaluate overall student learning by administering summative assessments before wrapping up a course term. Defined as "a judgment which encapsulates all the evidence up to a given point… [and] is seen as a finality at the point of the judgment" (Taras, 2005, p. 468), this type of assessment may occur at the end of a chapter, the end of a unit, or at the end of a semester or a program. While summative assessment can be applied throughout a term, we limit our discussion to the conclusion of a course term. Comparing summative assessment results from the previous cohort(s) or courses to the present one(s) is helpful in determining the effectiveness of a newly-adapted technique (Ifenthaler & Widanapathirana, 2014). Furthermore, an LMS-generated course statistical report can help identify the most and least engaging learning activities, in addition to the most and least accessed materials. With these findings, instructors may brainstorm ideas for course design improvements. Enlisting an instructional designer's professional expertise is highly recommended to develop innovative instructional strategies. Soliciting students' feedback about their learning experience may also provide incredible insight since they are the primary course users. Overall, instructors should always deploy interventions, being mindful of whether they improve student performance or not.

Available tools in LMSs and existing resources

To help deploy the aforementioned best practices throughout a course term, Table 1 lists built-in tools for three of the most commonly used LMSs—Blackboard, Moodle, and Canvas. While these tools may have a high learning curve and pose great challenges for first-time users, most LMS developers provide easy-to-understand tutorials and guidelines via support websites such as these:

- Blackboard Help for Instructor is available at https://help.blackboard.com/Learn/Instructor
- Managing a Moodle Course (a guide for teachers) can be found at https://docs.moodle.org/34/en/Managing_a_Moodle_course
- Canvas Instructor Guide is available at https://community.canvaslms.com/docs/DOC-10460

If it is unclear where one can find a guide for a particular tool, you may simply type the name of the tool in the website's search box. More often than not, instructors may rely on institutions to provide instructional designers to help them enhance learning and brainstorm about potential interventions and technology to adopt. As a side note, while we are aware of numerous online resources, e.g. "how-to" videos, we cannot vouch for their consistency or quality, and therefore cannot recommend them outright.

Table 1 Available built-in LMS tools and achievable actions through their respective tools.

Achievable Actions	Blackboard	Moodle	Canvas
Before the course term starts:			
• Schedule or post course events and reminders	Course Calendar	Calendar	Course Calendar, Scheduler
• Create pre-assessment	Test, Discussion Board	Quiz, Forum	Quizzes, Discussions
At the beginning of the course term:			
• Create a welcome message and emphasize the importance of frequent access to the course site	Announcement, Send Email, Course Messages	Course Summary, Announcements Forum (with email option)	Announcements, Inbox
• Define criteria and key performance indicators that consider students' achievement	Retention Center	Competencies, Learning Plan Templates	Learning Mastery Gradebook, Student Learning Mastery Gradebook
• Check students' last access to the course	Grade Center, Retention Center	Logs (within Reports)	Analytics, People
• Acquire course reports to find day/time patterns when students access the course most frequently	Course Reports	Logs (within Reports), Statistics	Course Statistics, Analytics

Note: The listed tools are from three of the most commonly used LMSs. Tool availability may vary by institutional LMS policy and procedure and whether enabled by LMS administrator.

Table 1 *continued*

Achievable Actions	Blackboard	Moodle	Canvas
During course term:			
• Discover at-risk students and monitor patterns over time	Retention Center	Analytics, Send Message, Logs	Analytics
• Identify students who miss assignments or submit late assignments	Grade Center, Retention Center	Grades, Activity Completion Report, Logs (by activity), Configurable Reports (performed at the LMS administration end)	Analytics, Gradebook
• Identify students who are less engaged in discussions	Performance Dashboard	Logs, Activity Reports	Analytics, Discussions, Speedgrader
• Identify students who perform poorly on exams/quizzes or tests	Grade Center, Retention Center	Grades, Quiz Reports	Gradebook, Analytics, Quiz Statistics
• Reach out to students showing early "at-risk" signs to offer support and scaffolding	Retention Center, Send Email (can be performed directly from Gradebook)	Quickmail, Send email directly from Grades	Analytics, Inbox, Send email directly from gradebook
• Analyze the validity and reliability of test questions and identify difficult questions for students	Item Analysis	Quiz Reports, Quiz Responses, Quiz Statistics	Quiz Statistics, Item Analysis (in Quizzes)
• Provide supplementary materials for difficult subjects personalized to students' current performance	Content Area, Course Reports, Adaptive Release	Lesson, Restrict Access, Competencies, Learning Plan Templates	Modules, Analytics, MasteryPaths
At the end of the course term:			
• Analyze overall course usage over the course term to identify the most or least engaging learning activities—the report will be useful in informing course-redesign decisions for the next course term	Course Reports	Completion Reports, Activity Reports, Course Participation Reports, Configurable Reports, Logs	Course Statistics, Analytics
• Administer a final exam, assignment, or project to assess overall student learning	Test, Assignment	Quiz, Assignment	Quizzes, Assignments, Quizzes.Next (in beta)
• Administer an exit survey to gain students' insights regarding their learning experience	Survey	Choice, Feedback	Survey

Note: The listed tools are from three of the most commonly used LMSs. Tool availability may vary by institutional LMS policy and procedure and whether enabled by LMS administrator.

Conclusion

Technology is not a panacea, it only amplifies current processes and practices. In this paper, we have offered compelling support for what LA can provide to boost the abilities of instructors in higher education. In particular, LA offers instructors tools to enable them to confirm their observation in much less time. More importantly, LA offers instructors the ability to become much more proactive by providing relevant feedback in near real-time. We have also given several easy-to-implement suggestions to assist instructors who wish to experiment or adopt LA in the classroom environment. These suggestions are ready to implement with a few process changes. While this requires advanced planning, our experiences have shown that such investment in time is well worth the saving during course execution. Learning analytics also provides another means for assessing the efficacy of teaching and learning practices. Moreover, LA provides a way for instructors to engage in their own research with relatively little investment as much of the infrastructure already exists in higher education vis-a-vis the proliferation of LMSs. This confirms the imperative role of LA now emerging within higher education and the urgent need to explore its potential in reaching the ultimate goal of promoting academic success.

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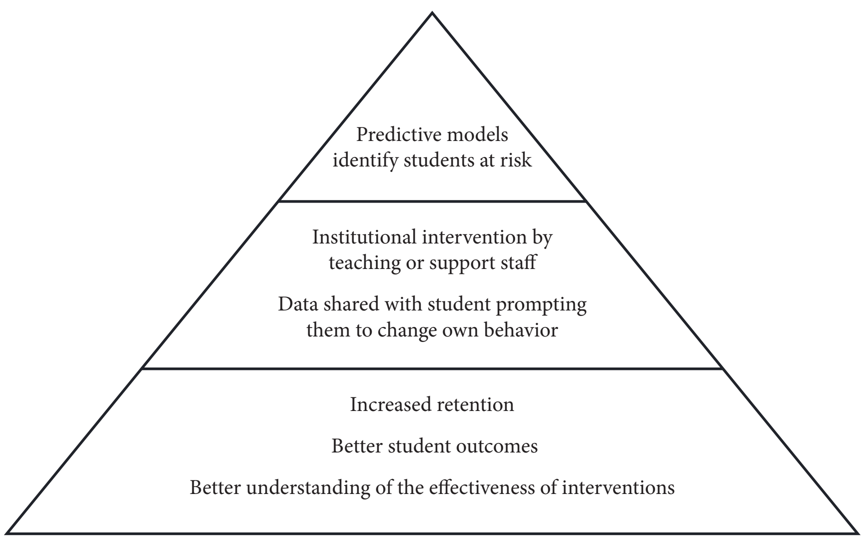
Appendix



Appendix A Open learning analytics architecture in higher education through predictive models proposed by Sclater and Mullan (2017).