

CHAPTER 10.

WHEN LEARNING OUTCOMES MASK LEARNING, PART 1: THE PROMISES AND PITFALLS OF LEARNING ANALYTICS

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In 2006, the U.S. Commission on the Future of Higher Education released a report interrogating and criticizing American universities for failing to adequately prepare students for the demands of their future careers. The report's authors claimed, "As other nations rapidly improve their higher education systems, we are disturbed by evidence that the quality of student learning at U.S. colleges and universities is inadequate and, in some cases, declining" (Spellings, 2006, p. 3). They noted that this is a crisis, not just of learning, but of institutional transparency, explaining that the current "lack of useful data and accountability hinders policymakers and the public from making informed decisions and prevents higher education from demonstrating its contribution to the public good" (Spellings, 2006, p. 4). University administrators across the U.S. have since scrambled to collect and analyze student data that could be used as evidence of the educational rigor of their programs and thus demonstrate that students at their institutions are achieving desired learning outcomes.

Compiling the data necessary to analyze an entire institution's educational outcomes is a large, complex endeavor requiring significant labor and resources. To make this a more manageable, affordable, and efficient endeavor, many administrators turned to learning analytics (LA), a type of educational Big Data that includes "the measurement, data collection, data analysis, and reporting of data about learners and their contexts" (SoLAR). LA refers to any tools and/or methods for using automated algorithms to make meaning from large and complex sets of data generated from user activities in digital learning environments.

To deploy LA at the institutional level, universities needed educational data. And not just demographic data or enrollment data; they needed data generated in the classrooms themselves. Fortunately, for many universities, administrators already had access to a trove of educational data, specifically data mined from

the institution's learning management system. Learning management systems (LMSs)—also known as course management systems—are online learning systems and platforms designed to create and host digital learning environments for both face-to-face and online courses (Salisbury, 2017). Because LMSs are typically designed for university-wide implementation and are thus used in courses across disciplines and colleges, more often than not, a university's LMS is also its largest and most comprehensive repository of educational data. So while LMSs aren't the sole place where LA can be deployed, they are certainly an attractive host of these operations.

LMSs became popular in the 21st century, when open-source LMSs with internal networks, like Moodle™ and then BlackBoard™, were introduced onto the higher education marketplace. For administrators, the introduction of LMS technology offered new (albeit expensive) opportunities for streamlining educational and institutional operations using data-driven decision-making. According to Hamish Coates et al. (2005), equipped with the data infrastructure afforded by an LMS, administrators could “reduce course management overheads, reduce physical space demands, enhance knowledge management, unify fragmented information technology initiatives within institutions, expedite information access, set auditable standards for course design and delivery and improve quality assurance procedures” (p. 24). Essentially, LMSs promised to empower university administrators with “a hitherto undreamt-of capacity to control and regulate teaching” (Coates et al., 2005, p. 24). In doing so, LMSs provide the structure for a top-down model where the institution is able to make decisions without necessitating student involvement.

The most popular LMSs among higher education institutions today are those that are pitched by developers and educational associations as state-of-the-art, data-powered mechanisms for helping administrators, educators, and students increase educational accessibility and foster student success while simultaneously streamlining course management and data mining efforts. As recent scholarship critiquing the Big Data boom in higher education has shown, however, once such programs are integrated, LMSs almost always fall short of their initial promise (Crawford et al., 2014; McKee, 2011; Reyman, 2010).

In much of the research on data-driven assessment technologies, the limitations of LMS-based LA are framed as temporally-bound problems that will be solved once technology inevitably progresses. By focusing criticism on the limitations of today's technology or the improper application of LMS programs, however, we as teachers and administrators in higher education leave unquestioned the assumption that these assessment technologies actually have the capacity to accurately and adequately measure student learning (Aguilar et al., 2021). In this chapter, I critically interrogate the promise at the heart of LA—namely, that it will make learning more personalized while simultaneously holding institutions accountable

to concrete standards—and argue that such a promise is necessarily unfulfillable. The underlying algorithmic structures for analyzing data are simply incapable of accounting for the complex and multi-faceted realities of student learning.

THE (UNFULFILLABLE) PROMISE OF LEARNING ANALYTICS

How do learning analytics (LA) work? Essentially, LA is an algorithmic process that relies on data mined from user activities on a platform or from student-generated data to assess and make predictions about student learning. The algorithm processes data from course materials like assignment submissions, exam and quiz answers, and online activities such as page views, clicks, and timestamps. Specifically, these machine learning algorithms sift through data to identify traces of “student learning” that can be aggregated across assignments in a course, across many students in a single course, and/or across many courses in an institution and then used as evidence of individual learning performance.

LA is methodologically contingent upon the belief that an objective measure of student effort and learning can be gleaned from digital traces. In 2012, the U.S. Department of Education released the report “Enhancing Teaching and Learning through Educational Data Mining and Learning Analytics,” claiming that LA could “predict” students’ chances of success by comparing data said to represent a student’s digital engagement with predetermined standards for what a successful or unsuccessful student’s individual digital engagement should look like: “Using these measures, teachers can distinguish between students who are not trying and those who are trying but still struggling and then differentiate instruction for each group” (Bienkowski et al., 2012, p. 20). This claim assumes educational data that have been mined and analyzed not only can be but are wholly representative of an individual student’s experience and engagement with digital material.

Such an assumption presents obvious gaps and problems of representativeness. For instance, the data points and patterns that the algorithm privileges and identifies as evidence of learning do not clearly map onto disciplinary understandings of what learning looks like. Further, the programs and data infrastructures undergirding learning analytic systems cannot account for students or educators whose activities do not register as digital signals. The problem here is not that there is not enough data, or that the analysis is not sophisticated enough, or that these systems are just preliminary attempts to use tools that will eventually, with greater refinement, accomplish the tasks set before them. Rather, the problem is that assessing learning with these technologies demands that learning itself be re-defined and reconfigured so as to be measurable by such a tool. Although the initial promise of LA is grounded in rhetorics of personalized learning, this promise comes with

the caveat that the mechanisms through which LA are deployed place constraints around what can be counted as learning. While all methods for assessment require that learning be reshaped to fit the assessment model, the process of reshaping learning can be more exaggerated when using LA for assessment of data-driven learning outcomes and less clearly connected to common learning goals like critical thinking and deep reading. To put this into perspective, I want to reiterate the examples that the authors of the U.S. Department of Education report provide of the types of data points that are collected by learning software: “minutes spent on a unit, hints used, and common errors” (Bienkowski et al., 2012, p. 20).

Just as instructors have to reshape their pedagogical approaches and materials to fit within the predetermined structure of their institution’s LMS or any other LA-based application, students also have to adjust how they approach the learning process. These patterns of refitting and reshaping learning to meet the demands of an LMS’s predetermined structure creates a feedback loop. Over years of continued use and refinement of educator and student behavior to meet its constraints, the system creates data that motivates those behaviors most amenable to the data generation and analysis functions it has been designed to fulfill. Importantly, the system never re-aligns itself with the student learning outcomes that the system was originally intended to measure and refine (Kuh & Ewell, 2010). Data thus become an end unto themselves.

To more clearly illustrate what qualifies as learning in LA contexts, and thus more clearly illustrate the risks that these systems pose for how we understand learning, I want to turn to a discussion about the data infrastructure and instructional practices behind the most popular and fastest-growing LMS for higher education in the US: Instructure’s Canvas.

LEARNING ANALYTICS IN THE CANVAS LMS

Developed and launched in 2011 by for-profit company Instructure, Canvas™ is a cloud-based LMS marketed for use in both K-12 and higher education contexts. What distinguished Canvas from other LMSs early on was that it operated as a Software as a Service (SaaS), a subscription-based and centrally hosted model of software licensing and development. The SaaS model means that users can access the Canvas software online, rather than through a downloaded, offline program. Similar to other SaaS like Google Drive and OneDrive, both of which operate via the cloud as well, Canvas’s infrastructure makes its program easy for users to access and for developers to update. While Canvas is not currently the only SaaS-operated LMS on the market, it was the first to offer cloud-based services capable of conducting large-scale data analytics and harnessing educational data to assess student learning. In the years following Canvas’s release, while

other LMS providers struggled to integrate similar data functionality into their services, Canvas was able to make its way to the forefront of LMS technologies and gain a significant advantage in the marketplace early on. As of 2021, Canvas is used by over 38 percent of higher education institutions in the US and is the fastest growing LMS on the market (“LMS Data,” 2021).

One of Canvas’s premiere features is the advanced set of tools it provides for data analytics. Literally marketed as being “like Moneyball for student success instead of baseball”—referencing the wild success of the Oakland A’s data-driven roster in 2002—Canvas’s analytics are designed to serve a number of different functions aimed at bettering the quality of student education (“Improving Learning,” 2019). In explanations of the potential benefits that universities can reap from using Canvas’s analytics, the feature that Instructure emphasizes most is the LMS’s capacity to help identify “at risk” students, which the program defines as “at risk of dropping out of a course, program, or institution” (“Glossary,” 2019).

The main mechanisms through which instructors using Canvas are supposedly able to identify “at risk” students are the “Course Analytics” feature, which includes compilations of data from all of the students in a single course and/or all of the students in multiple sections of the same course, and the “Student Analytics” feature, which includes data from individual students enrolled in each course. Both the course analytics and the student analytics rely on user-generated data, which are presented to instructors as data visualizations (mis)representing student engagement and progress.

Canvas’s data visualizations largely take the form of bar charts and line graphs. While the course and student analytics are largely similar in their graphical representation, Canvas also offers a student “Context Card,” which includes a more simplistic view of an individual student’s analytics. In addition to providing the student’s current grade, number of missing and complete assignments, and grades on the three most recent assignments, it includes a section titled “Activity Compared to the Class.” As the graphic in Figure 10.1 shows, these “activities” are represented as two, three-star rating visualizations that show the individual student’s page views and participation data in comparison to their classmates:

Both of the minimalist, star-rating data visualizations are offered to instructors without any details as to what exactly these visualizations mean. They provide no evidence of the mechanisms, data, or methods used in their production. The data used to construct the “Page Views” visualization is relatively straightforward in terms of what is being rated and compared (i.e., the number of discrete page views from each student’s account, which are also made available to instructors in more detail via a timestamped log of each time a student has accessed the Canvas course page). The data that the “Participation” visualization is meant to represent, however, are not implicitly clear for instructors using the context card feature.

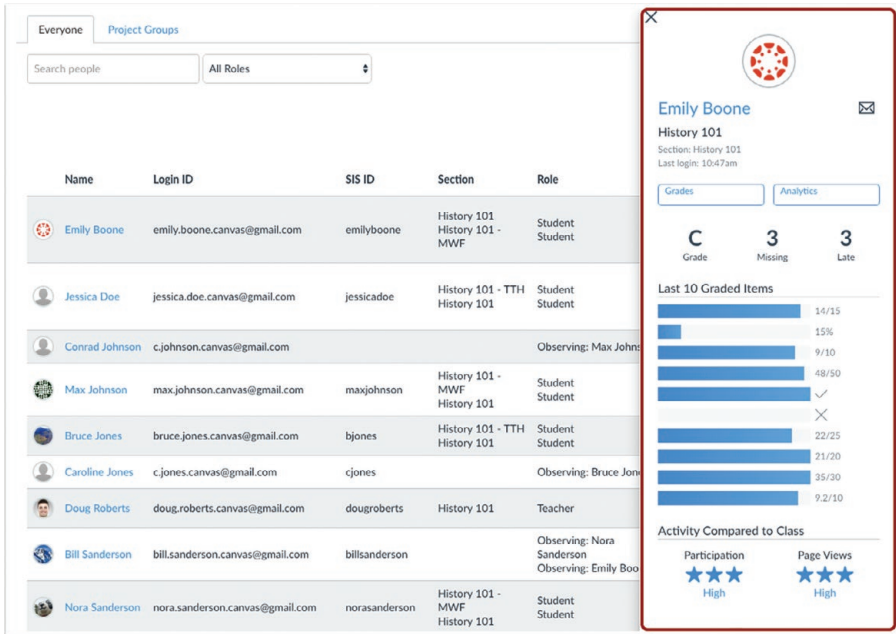


Figure 10.1. Graphic context card.

Despite the lack of explanation or context, the familiarity and clarity of the star-rating system grants the data visualization rhetorical power, encoding a particular kind of student success as a nudge to instructors. What counts as success and how it is represented in the context card is contingent on what is encoded into the algorithm. While Instructure does not provide an explanation of the context card mechanism on the Canvas portal, the Canvas Community website describes it as a “simplified overview of a student’s progress” that is based on grades and “standard page view and participation activity in course analytics” (Canvas Doc Team, n.d.).

To create participation scores, Canvas’s system compares the data that each individual student’s account activity generates with the equivalent data from their classmates’ accounts. The user actions that generate the data upon which these visualizations are based include: commenting on an announcement, submitting an assignment, submitting a quiz, initiating a quiz, joining a web conference, creating a wiki page, posting a discussion comment, and loading a collaboration page. Once data have been generated, they are then aggregated and fed into an algorithm that scores student participation in relation to their peers. The resultant participation scores are presented to instructors in the form of a three-star rating system labeled “Participation.”

The explanation provided on the Canvas Community website also includes an important qualifier as to the quality of the data represented in the context

card feature: Canvas's mobile app is not configured to collect data generated by student activities and actions (Canvas Doc Team, n.d.).¹ In other words, because the algorithm used to create student analytics cannot account for the mobile app's limited data functionality, for those students who mainly use the Canvas mobile app, their student analytics will be skewed. Importantly, a student might use a mobile device as their primary means for accessing Canvas for a number of reasons, including individual learning preferences or having limited access to WIFI, a laptop, or a desktop. For those students, in the space where student-generated data should appear, there will instead be potentially significant gaps in logged activity. When their data are run through Canvas's predictive models, these students can potentially receive lower participation and page view ratings than their peers whose activity data have been successfully harvested via the Canvas website. While instructors could theoretically account for these gaps in some other way, for instance, by asking students which type of device they use to access Canvas and then taking the device-type into consideration when assessing participation, this correction is unlikely given that these issues in data quality are not made readily apparent to instructors using the course and student analytics functions on their Canvas course page. It is also worth pointing out that, by posting this explanation of the context card on a page external to the Canvas website, developers are working against their own narratives that LMSs are self-contained systems. Even if instructors were able to find and access the information that is posted on the external Canvas Community website, they would be hard pressed to find detailed explanations about how Canvas's LA work.

Just as Canvas's analytics fail to account for data generated via the mobile app, they also inevitably fail to account for non-digital activities. If, for instance, a student downloads the course assignments and syllabus, or prints out a PDF of course materials, perhaps for accessibility reasons, they may return to that printed or downloaded document many more times throughout the semester. However, because their page view and participation data will only show that they have visited the page once, Canvas's analytics will rate that student's activities as being less than, say, another student in the course who accesses course material just as frequently, but via a web browser.

These largely unaddressed issues with the quality and equity of student data are problematic, especially considering that Canvas posits its course and student analytics features as capable of predicting and preventing "at risk" students. Consider the following hypothetical example: An instructor using Canvas notices that a student has been automatically flagged by the system's course and

1 "Mobile data is not included unless a user accesses Canvas directly through a mobile browser, or if a user accesses content within the mobile app that redirects to a mobile browser."

student analytics features as potentially “at risk” (for instance, by highlighting their name in red in the gradebook). The instructor clicks on the student’s context card and sees that, according to the system’s analytics, the student has a low page view ranking (one star out of three), a low participation ranking (two stars out of three), and has not submitted anything for an assignment that is now overdue. If the course is small enough in terms of student enrollment, and if the semester is far enough along that the instructor knows the student personally, the instructor might realize that the student has not shown up to class for the past few sessions. Wanting to investigate further, the instructor checks the student’s activity records and finds that the student has not generated any new data for two weeks. Assuming the student has not recently logged onto the course Canvas site, the instructor could then triangulate that perhaps the student is experiencing some distress and send a follow-up email. If the class is large or it is early in the semester, and the instructor is not familiar with the student, however, the likelihood of them recognizing this student as being at risk drops significantly. Now, imagine that there is a student who has been regularly attending class, but experiences perpetual anxiety about her performance, leading her to check the course’s Canvas page frequently. Because she has generated a lot of data on the Canvas website, she is not flagged by the system. Her high participation and page view rankings mask the difficulty she’s having, preventing the same kind of outreach more “obviously” struggling students would receive.

There are a number of factors that could contribute to a false positive or negative in Canvas’s analytics: mental health, technical difficulties or limitations, group work, or offline (“analog”) work. Identifying and correcting a false positive or negative is difficult, however, given how opaquely Canvas’s Course and Student Analytics are structured. While analytics for individual students are made available to instructors, those same analytics are not available within the student view. In other words, students cannot see the data that they themselves have generated. On the one hand, opacity could be a benefit because students are less likely to game the system by artificially manipulating their data. However, it poses an even larger ethical dilemma: Without disclosing the types of assessment mechanics of the Canvas website to students in the course syllabus, for example, students may not be aware of how (or even *that*) their digital behavior is influencing not only their instructor’s perception of them but potentially their course grade as well. Leaving students unaware of how their activity is being represented to instructors renders them unable to address inconsistencies, errors, or gaps that may arise across their own Canvas data.

The idea of tracking student activity for assessment purposes resonates with a movement in writing assessment toward labor-based contract grading. At their most basic level, labor-based grading contracts are a form of writing assessment

that privileges student work, or labor, done for the course (i.e., reading, writing, reflecting, discussing, assessing) over subjective judgements from instructors and peers as to the quality of student writing. Essentially, the more labor that students do for the course, the better their grade will be. Scholarship from Asao Inoue (2019) frames labor-based contract grading as a powerful tool for antiracist writing assessment. Inoue (2019) argues that, because labor-based contracts count all labor as equally valuable when determining student grades, they help “build equity among diverse students with diverse linguistic competencies since it is a grading system that does not depend on a particular set of linguistic competencies to acquire grades” (p. 132).

Mapping the ideas central to labor-based contract grading onto the LMS learning analytic model, we can see a number of parallels emerge. Both LA and labor-based contract grading are framed rhetorically as pedagogical tools for making classroom environments more inclusive and for helping empower student learners to achieve course learning goals. Further, both assessment practices use records of student activity to gauge student progress toward course learning goals.

While both models of assessment are built upon the same promise—namely, that they can help instructors teach more equitably and effectively—their underlying methodologies reveal stark differences: When constructing a labor-based grading contract, instructors and students have a significant degree of agency to decide what counts as labor. When using course and student analytics on an LMS like Canvas, however, students are granted no agency to decide what data count as effort or labor, nor can they intervene in their own assessment. Returning to the notion of using LA as a lens into students’ affective experience, we can see how LMS might then create risky learning environments wherein individual students, coded as users, are compared and assessed.

DATA QUALITY AND THE FUTURE OF DATA ANALYTICS

Over the past few years, some schools have begun using their LMS software as a tool to detect cheating retroactively by using data mined during exams and without student consent. New York Times contributors Natasha Singer and Aaron Krolik (2021) have investigated Dartmouth’s use of Canvas for detecting academic dishonesty. They found that Dartmouth’s Medical School had accused 17 students of cheating with evidence that had been identified using automated systems for gathering user activity data. Singer and Krolik (2021) explain,

While some students may have cheated, technology experts said, it would be difficult for a disciplinary committee to distinguish cheating from non-cheating based on the data

snapshots that Dartmouth provided to accused students. And in an analysis of the Canvas software code, *The Times* found instances in which the system automatically generated activity data even when no one was using a device.

Questions about the quality of data are rarely at the forefront of institutional discussions around LMS adoption. This lack of attention toward the Big Data end of Canvas is in part a product of the way that data privacy policies get configured in LMS software. For students, informed consent with respect to LMS data practices and policies becomes tacit upon enrollment. When universities subscribe to a particular LMS, they are not only giving consent for their own institutional data to be harvested, but they are also granting consent on behalf of their staff, faculty, and students. This practice of granting consent-by-proxy raises important ethical issues around data practices, especially in terms of what data are made visible and for whom. These issues are compounded when we consider the issues with data quality illustrated earlier: Many students and instructors are unaware of the data being collected.

It is important to recognize that, while not all instructors are currently using LA to track and assess students' learning progress (and while these features may not yet be perceived as critical to the system's functionality), there continues to be more widespread uptake among educators of features like the student context card, especially in the wake of the pandemic as instructors become more familiar with the Canvas platform and gain experience facilitating more of their teaching via the Canvas LMS. As high-enrollment courses and online-only courses become more prevalent on college campuses (a parallel change that is also a result of increased demands for greater efficiency and access in higher education), instructors may find themselves ever more inclined to use Canvas's LA to gauge their students' progress and effort. Their assessments will be (whether they know it or not) tied directly to the capacity of the LMS to track and analyze student data.

LA will soon be (if they aren't already) knocking on the door of WAC practitioners around the nation. As Mike Palmquist (2020) notes, "It seems likely that we will see a significant emphasis on the development of analytics tools that draw on data from student writing, their other behaviors in their courses, and their academic and demographic backgrounds" (p. 64). It's critical that WAC practitioners pay attention to these developments and anticipate the ways in which they will impact the writing classroom. It is our responsibility to investigate how LA function at our own institutions and to learn how (and what) student data gets packaged and presented to instructors so that we can engage in critical conversation with faculty about the digital contexts within which they are teaching and students are writing. When talking to faculty about responding

to and evaluating student writing, for instance, WAC leaders should create space to discuss the ways that their institution's LMS shapes the assessment process, including LA functions like Canvas's context card.

LMSs are not pedagogically neutral technologies, but rather, through their very design, they influence and guide teaching. Data-driven learning assessment, and LA more broadly, necessitate that higher education agencies, including instructors, students, and administrators, try to normalize not only what success looks like in the classroom and university, but also how students can move across educational spaces and how instructors can engage with students. The standards of success built into LMSs and other LA-equipped platforms are grounded in subjective claims with real material consequences. As Trevor Pinch (2008) argues, "Standards are rarely simply technical matters; they are powerful ways of bringing a resolution to debates that might encompass different social meanings of a technology. Standards are set to be followed; they entail routinized social actions and are in effect a form of institutionalization" (p. 473). Not only does this limit the visibility of non-digital actors, but it simultaneously promotes a fabricated perspective of student experience because the algorithmic outputs of the system are always already contingent on subjective agencies that produced the parameters for data interpretation.

Despite the myriad conveniences LA platforms afford instructors (especially in terms of streamlining the management and distribution of course materials), the reliance on algorithmic structures for analyzing data will always fail to account for the complex and multi-faceted realities of student learning. Far from revealing the realities of student learning, LA creates and deepens blind spots around how instructors can best "see" student learning, all while fostering misconceptions about what counts as learning in the writing classroom. As a mode of assessment, LA—with its reliance on predetermined standards for assessing learning and opaque methods for surveilling student work—ends up constraining rather than empowering student learners.

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