Do No Harm: A Balanced Approach to Vendor Relationships, Learning Analytics, and Higher Education

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Abstract

The field of learning analytics holds considerable promise for higher education, with reports of successful uses now emerging in selected institutions. At the same time, critics have expressed concerns regarding privacy, ethics, and intrusions into teachers' pedagogy. Without attentive planning, higher-education professionals applying learning analytics may inadvertently undermine their institutions' core teaching and learning missions. The authors offer a framework for moving forward with learning analytics, organized around three principles: (a) Institutions should take the lead in their conversations with vendors, emphasizing the distinctive values of higher education; (b) learning analytics data should be balanced with other forms of evidence that analytics cannot capture, especially participant experiences; and (c) successful implementations will leave room for adaptations by people on the ground—to notice what is working and integrate the tools into their practices. Only by empowering students, faculty, and staff can these tools fulfill their potential in higher education.

Keywords: Learning analytics, higher education, activity systems, student success, advisor tools

Big data is a broad term that refers to the massive amounts of digital information that are captured and used to personalize content, predict behavior, and design interventions. Big data has been leveraged in fields such as the physical sciences, marketing and business, and, more recently, higher education (Boyd & Crawford, 2012; Clow, 2013; Wilson, Thompson, Watson, Drew, & Doyle, 2017). Big data applied to education is often referred to as *learning analytics* (LA). Higher-education professionals are increasingly utilizing LA, "to recognize challenges early, improve student outcomes, and personalize the learning experience" (Johnson, Adams Becker, Estrada, & Freeman, 2015, p. 12). The timing seems right for this development, because of the convergence of several trends: (a) online learning interactions, social media, and traditional transcript and demographic data; (b) a growing sophistication in data analysis and predictive-modeling techniques; and (c) the increasing pressure in higher education for efficiency, scalability, accountability, and competitive advantage (Clow).

Scaling up LA implementations can affect faculty, staff, and students in a variety of ways. Learning management systems (LMS) such as Moodle, Blackboard, or Canvas, used for residential, blended, and online courses, create data sets of learning activity and academic performance. Individual instructors may consult LMS data on student activity to determine a class-participation grade. Advisement tools that draw on academic history and admission credentials can prompt advisors to make specific recommendations to students, who in turn can receive nudges in the form of texts, emails, and phone reminders to complete assigned class activities or university logistical requirements.

Two sites of successful LA implementations are Georgia State and Purdue Universities. Since 2012, Georgia State has increasingly relied on predictive analytics to help identify and intervene with at-risk students: “The institution’s systems update student grades and records every night, and they review 800 risk factors for each of the 50,000 students on a continuous basis” (Dimeo, 2017, para. 3). Georgia State has attributed increased graduation rates to LA-based interventions (Dimeo).

Purdue’s homegrown Course Signals application operates at the course level, alerting faculty and students to behavior that may be putting students at risk of failure. According to researchers at Purdue,

> Course Signals relies not only on grades to predict students’ performance, but also demographic characteristics, past academic history, and students’ effort as measured by interaction with Blackboard Vista, Purdue’s learning management system. The outcome is delivered to the students via a personalized email from the faculty member to each student, as well as a specific color on a stoplight—traffic signal—to indicate how each student is doing. (Arnold & Pistilli, 2012, p. 1)

Like Georgia State’s program, Course Signals at Purdue has led to improved learning and retention in individual courses (Arnold & Pistilli, 2012; Wilson et al., 2017).

Although such implementations have been promoted for their potential to improve increase student success, they have also been challenged and debated. LA tools raise concerns about privacy, ethics, and constant monitoring. Additionally, critics warn that predictive analytics, whose predictions are often based primarily on past performance and student histories, might reproduce some of the systemic inequalities that education is supposed to challenge (Boyd & Crawford, 2012; Pardo & Siemens, 2014; Reed, 2017). For example, concerns were raised initially by some faculty members that Georgia State’s system might encourage certain students to enroll in less rigorous majors (Dimeo, 2017).

Given this mix of potential benefits and challenges, combined with the “adapt or die” pressures common in higher education (White, 2013), many educators are uncertain about how to navigate this fast-changing landscape. As a response, we offer a holistic framework for adopting LA applications in a balanced way, including three guiding principles:

1. Institutions should take the lead in their conversations with vendors, emphasizing the distinctive values of higher education.
2. Learning analytics data should be balanced with other forms of evidence that analytics cannot capture, especially participant experiences.
3. Successful implementations will leave room for adaptations by people on the ground—to notice what is working and integrate the tools into their practices.

We offer a cautiously optimistic approach to learning analytics that reasserts the intrinsically human endeavor of higher education.

Partnering with Educational Technology Vendors

The adoption of learning analytics in higher education is sometimes compared to the use of big data in fields such as marketing and the physical sciences (Wilson et al., 2017). Fundamentally, all three sectors use large amounts of data to model likely behaviors, predict outcomes, and then suggest interventions based on these projections. Meteorologists, for example, rely on simulations from big data to model dynamic weather patterns, with direct implications for commerce, travel, and public safety. Businesses use big data to adapt marketing messages, personalize content for customers, enhance the customer experience, and build enduring relationships. Similarly, higher education can use LA data to provide extra support for at-risk students, personalize instructional content, and strengthen relationships with students.

At the same time, faculty and staff in higher education are uniquely charged with creating an environment that best supports learners along their academic paths. To be true to that core purpose, we must acknowledge the crucial ways that education differs from other fields.

Start with Higher Education's Distinctive Mission
If a marketing algorithm misses the mark and a potential customer is shown an inappropriate ad, a sale might be lost. If an educational intervention is based on a poor predictive model or sends a poorly worded message, a vulnerable student might be discouraged from completing a course or drop out entirely. LA-based applications must be effective in the aggregate, but they should also minimize negative effects on individuals.

By its nature, higher education is a cooperative enterprise, requiring investments and best efforts of multiple partners and stakeholders. Although educational-technology vendors bring important expertise to the table, all vendor partnerships must align with the mission and purposes of higher education. These purposes do include transactional exchanges of credentialing and certification but also a commitment to the deeper, longer-term growth and transformation of individuals, helping students achieve academic goals, and preparing them for new opportunities in life.

Interrogate the "Black Box"
Because of its quantitative and large-scale nature, big data can promise a seductive but problematic objectivity:

> This is a world where massive amounts of data and applied mathematics replace every other tool that might be brought to bear. Out with every theory of human behavior, from linguistics to sociology. Forget taxonomy, ontology, and psychology. Who knows why people do what they do? The point is they do it, and we can track and measure it with unprecedented fidelity. *With enough data, the numbers speak for themselves*. (Anderson, 2008, para. 7, emphasis added)

Anderson's last sentence, "With enough data, the numbers speak for themselves," would suggest a neutral and unbiased role for LA applications. These applications, however, depend on underlying models, algorithms, and assumptions about how people learn. Adaptive learning systems, for example, often make qualitative designations about learner competence, such as whether a learner is a novice, proficient, or expert, based on assumptions about question difficulty and test properties. These decisions require human judgment; for instance, how many "difficult" questions a student has to answer correctly, and in what time frame, to be designated an "expert." The numbers "speak" through hidden algorithms and program-designed features. This process has been referred to as the "black box" of adaptive learning (Blumenstyk, 2016). In working with LA companies, higher-education professionals should interrogate these underlying pedagogical assumptions.

Consider Privacy
LA applications also raise important and complex privacy concerns that higher-education institutions are confronting. There are now "unprecedented opportunities to create radical improvements in learning and educational achievement, but also conditions under which information about learners is collected continuously and often invisibly" (The Asilomar Convention for Learning Research in Higher Education, 2014). Some will argue that because of the ubiquity of social media, today's students are used to sharing personal information and that privacy concerns are exaggerated (Else, 2017). However, data ownership and privacy continue to be important considerations because of the potential implications for a student's academic career and beyond (Roberts, Howell, Seaman, & Gibson, 2016). Because educational-technology vendors typically do not voluntarily expose the weaknesses, limitations, or ethical tensions of their products and services, it is ultimately our responsibility as higher-education professionals to examine the complex ramifications for all users—students, faculty, advisors, and other staff members.

Taking the lead in conversations with educational-technology vendors does not mean being obstinate or belligerent. In today's context, partnerships with educational-technology vendors are both inevitable and often highly beneficial for students and instructors. At the same time, it is crucial that universities enter these conversations prepared and willing to advocate for the core values of higher education. Because academia can be slower to adopt new technologies than other sectors, vendors will often rely on examples from other fields when suggesting the benefits of LA for higher education. We should be wary, however, of adopting a system developed for other industries and then retrofitted for higher education without asking critical questions about pedagogical alignment, privacy issues, potential risks to learners, and the full range of impacts on underserved and special-needs populations. We should keep an open mind but also be ready to push back with specifics when examples from other industries might not apply to higher education and its mission.

LA Data Cannot Tell You Everything

Education is a fundamentally human endeavor involving relationships, communities, co-constructed meanings, and life-changing interactions. Extant data sets, however, capture only a part of the full picture. We need to also pay attention to what is *not* captured in LA, or we risk "treating the data that have been gathered as the data that matter" (Clow, 2013, p. 692).

"Engagement" and the LMS

A case in point is the way that some tools interpret student engagement in terms of LMS usage data (Fain, 2016). Consider an instructor-facing dashboard, where colors are used to portray student risk levels. Red denotes students considered "at risk," based on lower levels of LMS interaction or lower performance on assignments. A color-coding scheme may help instructors identify at a glance those students who warrant closer attention. At the same time, the simple dashboard masks some potentially important complexity. In spite of some evidence that, in the aggregate, a correlation exists between LMS activity and higher grades (Fain), some strong students might actually exhibit *less* LMS activity because they process the content more readily or because they successfully draw on alternative resources online or offline. For any given student, LMS activity rate does not always equate to learning, nor does lack of activity necessarily suggest failure to learn. This nonlinear relationship harkens back to time-on-task research, in which time on task was found to account for only 1 to 15% of learning, due to students' varying reasons for engaging (Karweit, 1984).

Like learning, engagement is a complex concept with cognitive, affective, social, and behavioral dimensions (Sinatra, Heddy, & Lombardi, 2015). Reducing engagement solely to LMS clicks or quantitative measures of discussion posts will always portray an incomplete picture. Analytics can measure activity levels, but they cannot assess whether these behaviors reflect struggles with the content, frustrations with the teaching approach, boredom, technical challenges, prior mastery of the content, or important interactions occurring outside the LMS. Behavioral data is necessarily a sharp reduction or even distortion of experience, ignoring key elements in favor of what can be easily scaled and collected. We are wise to remember that "all that matters cannot be measured, all that can be measured does not matter" (Eisner, 2002).

Considering Context

Moving from the aggregate to the particular can be tricky. We should not assume that the data models apply in every case or tell us enough about any single case. For instance, faculty use of an LMS varies greatly across course formats (e.g., online, blended, residential); disciplines (e.g., science, engineering, social sciences, humanities); course level (e.g., introductory, doctoral); and pedagogical approach (e.g., direct instruction versus guided inquiry). If we lack the contextual understanding of how instructors and students *actually* participate in the course and use the LMS, our interpretations of what is happening, when based solely on the LMS data, can be limited and misleading. Without closer observation and direct check-ins, the LMS analytics may be oversold as representing something that they do not.

Behind every data point is a story, and, whether we consider it "small data" or ethnographic detail, these stories can add enormously to our understanding of aggregate data. Ethnographic approaches assume that we need more in-depth information to truly understand our subjects. "Thick data" (Geertz, 1973) about actual teaching and learning practices can inform LA models and help faculty and students make informed use of system recommendations. Data-driven applications without the messy stories of on-the-ground realities become vulnerable to imbalance, inaccuracy, and unhelpful interventions, at risk of being sidestepped or worked around by the participants themselves.

Even marketing professionals have recognized the value of deeper contextual data. Consider the case of LEGO. At one point in the 1990s, LEGO manufacturers were beginning to believe the increasingly common assertion, based on quantitative trends in sales data, that instant gratification through video games would soon make their more contemplative and quietly creative toys obsolete. However, confronted with the ethnography of a boy who seemed to defy the mold, they realized that 10-year-olds also liked setting difficult challenges and even defined themselves by overcoming them. LEGO focused on this insight and made its building sets *more* complicated rather than simpler, eventually becoming the world's largest toy maker. This critical realization required small observation, small data, local noticing, and fresh theorizing to create a new set of assumptions and meanings (Lindstrom, 2017).

Complementing LA Data with Qualitative Observations

Ultimately, we need tools that draw on LA data to work alongside qualitative data, both formal and informal. LA data absolutely provide perspectives on teaching and learning processes that were not readily apparent before. Additionally, learning from students about their actual experiences within courses, whether through surveys or personal interactions, provides further information. We should leverage what LA offers and also include the contextual understandings from the participants themselves.

Formal qualitative studies of lived experience are certainly one important route, albeit expensive and time consuming. We also suggest low-cost routine, systematic, local observations by faculty and staff. Examples include student check-ins via spot surveys, group discussions, and occasional interviews at points of advisement, extra help, or exiting the program. These low-cost but important local observations assess how well the teaching and learning process is working. Experienced instructors know to monitor the pulse of a class and build positive trust and chemistry, which in turn can lead to insights about helping individual students on paths to success. These context-bound qualitative perspectives should be included when LA applications are implemented.

To summarize: models and recommendations from LA data can be better than nothing—but they can also be *worse* than nothing if they systematically neglect other indicators and lead to unwarranted actions or harmful insertions into complex educational systems. The best LA implementations will balance aggregated modeling, close-up noticing, and thoughtful participation. Finding a way to do that cost effectively will be an important agenda for educators. Systems theorists call this management of complexity *satisficing* or *muddling through*. We call it *Do no harm*, as we work toward significant improvements by including LA data with other forms of useful evidence about teaching and learning.

Empowering the End Users

Designers of tools and systems have an implicit model of end users in mind. End users of LA tools are the faculty and staff attending to student success, as well as the students who may engage the tools directly or indirectly. When people interact with tools, they may feel either empowered to further action or disempowered and at the mercy of the tool. Good LA implementations will expand the action potential of end users and enhance people's sense of control and empowerment. For example, faculty members exercise agency and judgment when they review Turnitin findings and decide how to respond to an indication of plagiarism rather than relying solely on the finding of the tool. By taking into account their previous history with the student in question and other indications of intent, instructors are able to combine the data-driven alert with their own qualitative observations. Similarly, students exercise agency as they encounter a reminder email from an instructor or early-alert system—to read and reply or to ignore.

Encouraging Agency

In the current landscape, faculty may easily feel overwhelmed by the technologies that they are being asked to use. Concerns about monitoring and evaluating teacher performance through analytics might also challenge instructors' sense of agency in their classes. To see how this could play out in practice, recall the example where student engagement is measured by LMS interaction data. Instructor Insight is a commercially available tool intended to help administrators use LMS data to evaluate instructors.

> Schools have plenty of anecdotal evidence that points to their best instructors. But can you quantify it with data? This is exactly what Instructor Insight provides. We analyze data from the LMS every night and chart important actions like frequency of course access, timeliness of grading, activity in discussion groups and other key metrics. We even provide you with random snippets of grading feedback. Identify the actions of your best instructors. (Instructor Insight, n.d.)

If such a tool is used without a proper teaching context, an instructor could feel pressured to make arbitrary pedagogical changes; for example, adopting online discussion activity even though discussion had already taken place in the classroom. When performance incentives are based on a narrow data set, distortions in practice will likely follow, leaving instructors feeling even less agency and respect from the system.

Students face similar issues. Although all students benefit from corrective feedback and difficult conversations at key points in their development, insensitively administered feedback may discourage or alienate them. Human behaviors are not simple functions of motivation principles; people often respond in idiosyncratic and surprising ways. Consider the case reported by Straumsheim (2017) of an LMS dashboard that provided automated feedback determined by student performance. Researchers had assumed that the highest performing students would be the ones most motivated by the messages, yet it was actually the students with a B average or lower who used the system more. Moreover, messages assumed to be encouraging to the highest performing students—"you make it look easy," for students doing well—were actually discouraging to some, because they felt that their hard work and efforts were being discounted. This example demonstrates the importance of paying attention to actual experiences of the users of these systems and the ways in which they might differ from the intended outcome. More subtlety in messaging is obviously called for—the kind of message crafting routinely done by seasoned instructors.

LA Tools are Relatively "Young"

LA tools to fit human needs are now at the earliest stages of design. Interfaces and messaging are often based on oversimplified ideas about what motivates students and how they engage as learners. Customizing tools to human activity systems takes time and resources, including incorporating theories about persuasive technologies and user experience design (UXD) that are just now emerging (e.g., Filippou, 2017). As Fritz and Whitmer (2017) observed, the hardest part of their tool development was crafting the messages to students that were meant to invoke and maintain optimal motivation across time and for different conditions. Until better tools and interfaces are available, educators should continue to assume responsibility for ensuring the proper fit of the tools.

Fritz and Whitmer (2017) discuss a case at the University of Maryland, Baltimore County, that exemplifies this combined approach. Through the use of LMS data, they observed that student performance in course sections taught by a particular instructor was consistently higher than in other sections. Investigating further, they found that the key difference was the use of the "adaptive release" LMS feature, wherein completion of certain work triggers the release of further content through the LMS. Since this discovery, the practice of adaptive release has been shared formally and informally among faculty and is now a recommended best pedagogical practice at the university. Accordingly, they note the role of LMS data within a larger context of teaching and learning:

> [T]he *quantitative methodology* of learning analytics was used to identify a high LMS activity outlier instructor and the underlying effective practice. *Qualitative methodology* was then used to reverse

> engineer why AR [adaptive release] was effective. How and why to use AR was then shared with other faculty through informal presentations, an online screencast, and a more formal case study. (Fritz and Whitmer, 2017, para. 12, emphasis added)

In this case, the LMS data provoked cycles of inquiry and redesign, from noticing to theorizing to field testing and, finally, disseminating the innovative practices.

The strategy of adaptive release is promising but may not be appropriate for every situation; the possibility can be explored through ongoing inquiry that includes LA data and other forms of evidence. As another example, Williams, Yanchar, South, Wilson, and Allen (2011) examined how instructional designers in practice integrate evaluation concepts to improve courses; LA provides more data to identify promising strategies and empirically validate the use of those strategies in different situations (Reigeluth, Bunderson, & Merrill, 1978). Coupling LA modeling with local insights might suggest to faculty where to improve their teaching, instructional designers the course design, or advisors the timing and target of interventions. Educators might also take a large-scale view of data from a dashboard and notice a promising trend or practice. The deeper improvements will happen as we analyze how students process the content—with LA tools adding value along the way.

Tying it All Together: Two Visual Depictions

Figure 1 presents the implicit model underlying much of the conversation about LA, especially among vendors and LA advocates.

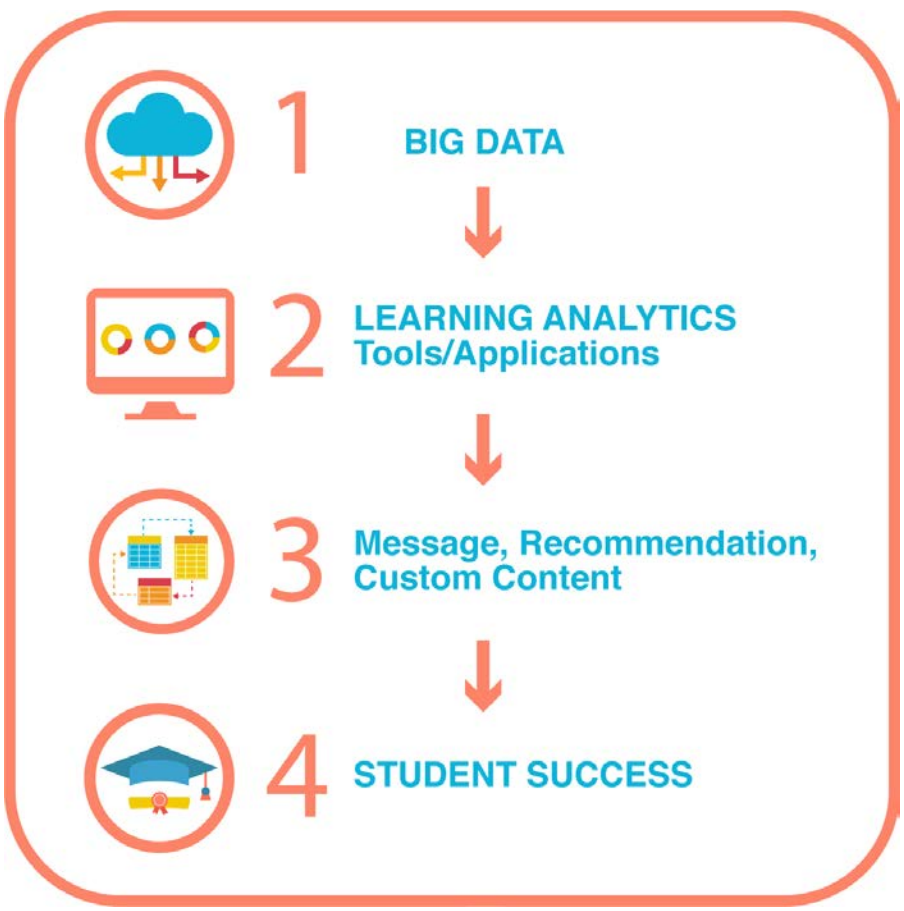

Figure 1. A technology-centric model: tools do the work of student guidance and advising.

This model is appealing in its simplicity and its data-centered logic. An advisor system uses big data to develop a model of student success, which is then used to guide individual students via direct messages—encouraging emails meant to keep students on track, or system messages with advice about upcoming decisions. Students may be routed onto a different learning path with adapted content, such as a helpful article, blog post, or video appropriate to the student's engagement or performance level.

A criticism of Figure 1, however, lies in its technological determinism: the tool and the data are doing the work. Notably absent are faculty and staff, who employ the tools and data. An example of this perspective can be seen in an *Inside Higher Ed* article on Georgia State's use of predictive analytics—in both the title and organization of the article. Titled "Georgia State Improves Student Outcomes with Data," the write-up does not mention until nearly the end (the last 11% of the article) that 42 new advisors were hired to work with students as part of this effort (Dimeo, 2017). The situation could more accurately be described as "Georgia State Improves Student Performance with Data, Better Processes, and Increasing Its Advising Staff." Also, as we have established, LA data as a sole source of evidence is needlessly narrow in scope.

Figure 2 addresses such criticisms by adding a parallel track of qualitative data, ranging from informal observation by attentive instructors to formal studies of student behavior. Unlike a solely tool- and data-driven model, educators enter the picture and play a role at every step—observing student activity and collecting qualitative data, integrating LA-based recommendations, and guiding students toward success. Steps, or stages, are discernible, from data analysis to practice to outcomes, but the tools and their magic are positioned as one part of the larger activity system.

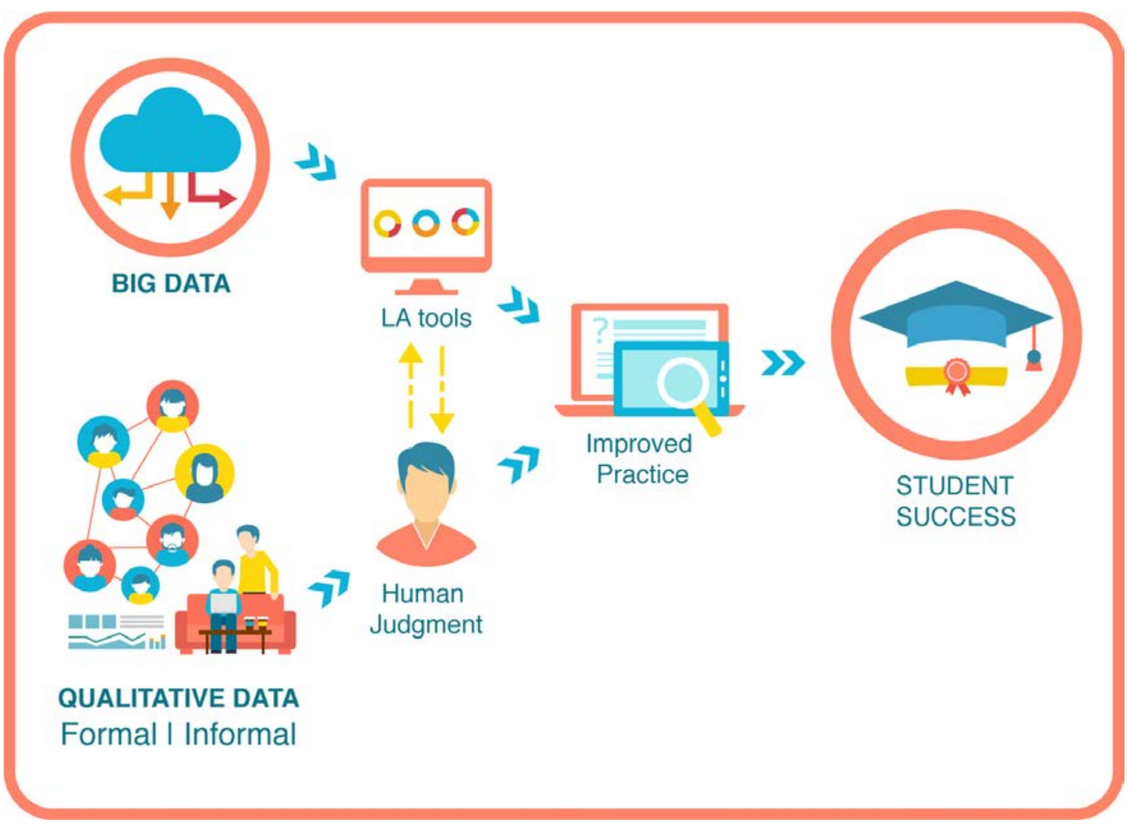

Figure 2. A human-systems model: humans and tools, fueled by different forms of evidence, converge and contribute to student success together.

Additional factors such as student buy-in and cooperation surely belong in the "improved practice" box, as do attentive instructors, well-designed courses, and invested and competent advisors. Other supports offered by the university also play important roles, such as offices of inclusion and diversity, accessibility services, and scholarships. On the learner side, networks of peers, mentors, and student support must also play a role. So much is hidden and implicit in any model; Figure 2 at a minimum moves us beyond the technology-centric mind-set depicted in Figure 1.

Human activity systems offer a response to the technocentric mind-set. Tools, no matter how powerful, are designed to help people work more effectively. As such, they are embedded and integrated into human activity systems. Cultural-historical activity theory (CHAT) examines how these human systems of activity operate as people divide work and create rules for operation, adopting tools and resources in pursuit of shared ends (Engeström, 2001). Adopting a systems view helps us rein in the powerful LA tools and frame their use within the larger context of human activity.

Conclusion

As Davis and Patterson (2012) have observed, "Big data is already outpacing our ability to understand its implications" (p. 15). We all—consumer, vendor, student, educator, higher education institution—exist in a reality of constant technological change. What is impossible technologically at a given time is taken for granted a few years later. Important questions lie just beyond our awareness, waiting to be asked as the right conditions unfold. This is how thinking and tools work together, playing off each other and pushing practice in zigzagging but overall productive directions. Trying to foresee all the implications of any new educational technology or approach will likely keep us from investing in anything at all. At the same time, given that technology is moving faster than our current understandings, avoiding critical questions about the technologies we are using in higher education is equally problematic.

It is a truism of technology generally and educational technology specifically that we tend to overestimate the short-term advantages while underestimating the long-term impacts. In this vein, Clow (2013) argues that the "[t]he opportunity afforded by learning analytics is for educators to refuse to be overawed by the process, to understand the tools and techniques, their strengths and limitations, and to use that understanding to improve teaching and learning." (p. 693). We offer this paper in the spirit of Clow's charge. First, institutions must better advocate for the teaching and learning mission by taking a leadership role, asking critical questions, and ensuring that diverse perspectives are part of the conversation. Second, much important information cannot be captured and represented by LA data, so successful implementation will pay attention to "smaller" forms of data such as participant voices, practices, and meanings. Third, although much of the emphasis in the current discourse is tool-centric, how people respond on the ground and in everyday life is more important than the tool or data itself. Successful implementations of LA will not "just happen." We must ensure that tools, processes, and implementations fit the needs and organizational cultures of higher education.

The conceptual reframing from technocentric to human-centric has pragmatic consequences. If we are careless and assume that LA interventions are easy and obvious, the tools could lead to reverse outcomes as they risk de-motivating, frustrating, and distracting students, instructors, and staff and ultimately work against the larger mission that they are intended to serve. However, if we are careful, mindful, and intentional in design and deployment, respecting the complexity of participants and their complex interactions, LA tools can realize their full potential.

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