Title

A matter of trust: Higher education institutions as information fiduciaries in an age of educational data mining and learning analytics

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Citation

This is a preprint. Please cite to the final version:

Jones, Kyle M. L., Rubel, Alan, & LeClere, Ellen (forthcoming). A matter of trust: Higher education institutions as information fiduciaries in an age of educational data mining and learning analytics. *Journal of the Association for Information Science and Technology*. https://doi.org/10.1002/asi.24327

Abstract

Higher education institutions are mining and analyzing student data to effect educational, political, and managerial outcomes. Done under the banner of "learning analytics," this work can—and often does—surface sensitive data and information about, inter alia, a student's demographics, academic performance, offline and online movements, physical fitness, mental wellbeing, and social network. With these data, institutions and third parties are able to describe student life, predict future behaviors, and intervene to address academic or other barriers to student success (however defined). Learning analytics, consequently, raise serious issues concerning student privacy, autonomy, and the appropriate flow of student data. We argue that issues around privacy lead to valid questions about the degree to which students should trust their institution to use learning analytics data and other artifacts (algorithms, predictive scores) with their interests in mind. We argue that higher education institutions are paradigms of information fiduciaries. As such, colleges and universities have a special responsibility to their students. In this article, we use the information fiduciary concept to analyze cases when learning analytics violate an institution's responsibility to its students.

Keywords: higher education, learning analytics, student privacy, trust, information fiduciary

Learning analytics (LA) is the "measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs," (Siemens, 2012). Higher education institutions (HEIs) are investing substantial resources in LA, arguing as they do that analyzing data and information about students will help them address accountability pressures (e.g., from legislators), increase retention, decrease time-to-degree, and raise graduation rates. Some proponents suggest that LA will reveal student behaviors that could inform pedagogy and help develop learning support systems (e.g., personalized curricula, just-in-time interventions).

The move toward LA is in part due to the ease by which HEIs can mine student data. HEIs aim to capitalize on growing troves of data that are increasingly exhaustive, fine-grained, combinable (i.e., relational), extensible, and scalable in part because the data (and data-analysis tools) are widely available (Laney, 2001; Goff & Shaffer, 2014; Kitchin, 2014; Lane & Finsel, 2014). Higher education and educational technology news sources call student data the "new oil" or a "gold mine" in terms of its value to HEIs (see Asay, 2013; Mayer-Schönberger & Cukier, 2013; Peters, 2012; Rotella, 2012).

With these data and the new technological advancements that enable their analysis, HEIs are adopting new epistemologies that reconsider how to measure student success, intervene in student life, and manage bureaucratic institutions (see boyd & Crawford, 2012; Gantz & Reinsel, 2011). A powerful example of this comes from Unizin, an institutional consortium comprised of 25 public universities and university systems serving over 900,000 students (Unizin, 2018a). Part of Unizin's mission is to develop what they call "the world's largest learning laboratory" (2018b, para. 7), which builds upon the Unizin Data Platform (UDP) and the Unizin Common Data Model (UCDM). The UCDM "organizes a standardized data repository for each Member by combining the silos of teaching and learning data into a set of managed and extensible resources" (2017b, para. 11). Unizin members are encouraged to provide "demographic, historical, curricular, performance, and behavioral data" to support the operation of "the largest, richest, and broadest collection of learner data in higher education" (Unizin, 2018d). Aggregating "all the data" to serve computing-intensive analytics (rather than traditional educational assessments or insights drawn from small, institutionally-bound datasets) is preferable and profitable (DeVaney, 2016).

Unizin's data warehouse is socially and financially valuable to the 25 HEIs and associated "university researchers, faculty, application developers, and other staff" who can access and mine data to meet institutional goals (Unizin, 2018c, para. 3). It is also valuable to the many non-member third parties who may access the warehouse via contract with Unizin. Companies like Barnes & Noble, Pearson, and Google have developed digital tools and technologies to support Unizin's broad LA goals. BNED LoudCloud (a Barnes & Noble Education company) created a predictive model called "LoudSight" to identify at-risk students by analyzing over 200 datapoints collected across many different campus systems (Unizin, 2017a). Pearson's extensive eBook catalog and adaptive learning products are offered to Unizin member institutions at a significant discount, which provide institutions "valuable insights into students' learning activity" culled from student interaction data (Unizin, 2016).

While many of these partnerships would indeed prove useful for institutions, it is not clear if benefits will redound to students, in the near future or at all. In fact, in Unizin's five-plus-year existence, few tangible learning-related outcomes have emerged and the efficacy of LA as a whole is under debate; one systematic literature review found that "there is little evidence in terms of [LA] improving students' learning outcomes" (Hill, 2017; Straumsheim, 2015; Viberg, Hatakka, Bälter, & Mavroudia, 2018, p. 102). The possibility that LA does not serve student interests is particularly troublesome insofar as the edifice of LA is built on stores of sensitive, identifiable student data. Proponents of LA often argue that HEIs have a positive "obligation to act" (Willis, Campbell, & Pistilli, 2013) on available student data, but the source and extent of the obligation are unclear, especially if many of the benefits of LA redound to institutions rather than individual students (see Prinsloo & Slade, 2017; Rubel & Jones, 2016). Our aim in this paper is to argue that HEIs are paradigms of information fiduciaries. As such, the institution has a special responsibility to its students. Institutions must protect student data and use them in ways that first and foremost serve students' interests and not degrade the trust students place in their institution. If institutions adopt a fiduciary role and its responsibilities, data and information practices and the policies that inform them will evolve to be more student centered and ethically justifiable. A cumulative effect may be that the educational technology vendors whom institutions retain for services will be moved to adjust their own practices in order to maintain their financially lucrative contracts.

We begin by outlining LA practices and goals, especially those that present moral problems. We then draw on Jack Balkin's (2016) concept of information fiduciaries, which explains ways in which entities holding data may incur special obligations to data subjects. We expand the concept as it applies to HEIs in an era of educational data mining. After developing the concept, we use it to examine three case studies. First, we discuss loopholes in FERPA that have increased access to student data by third parties who benefit from such access. Second, we highlight how instructors can surveil student behaviors and gain access to revelatory data and information via eTexts. Finally, we analyze how advisors use predictive algorithms to push students toward courses and degree programs for which they have a higher probability of success. For each of these cases, we critique ways in which new flows and uses of student data violate student trust and the responsibilities universities incur as information fiduciaries.

Educational Data Mining and Learning Analytics

Goals of Educational Data Mining and Learning Analytics

Undoubtedly, investments in LA infrastructures are costly. What do LA advocates seek to achieve with their investments in data aggregation, mining, and analytics? Rubel and Jones (2017) characterize the aims according to two categories. First, improving learning outcomes (i.e., what and how students learn) is a key target, and descriptive statistics, predictive modeling, algorithms, and machine learning are the primary means to these ends. To varying degrees, these things provide opportunities for institutional actors and educational technology systems to personalize students' educational experiences according to their socioeconomic profile, personality traits, personal interests, and educational dispositions (Siemens, 2013). Among other things, this set of tools can equip instructors with information to provide just-in-time interventions; they can also tweak the release of course content and construction of assessments based on a student's past performance and predicted levels of academic achievement.

Second, LA are economic and political tools. Data-driven insights may help increase institutional efficiency and effectiveness; some of these insights will impact teaching and learning directly or indirectly, but primarily they will help institutional actors run a highly bureaucratic institution that relies on vast and varied resources. Assuming that *some* gains are made in student learning, retention yields, graduation rates, and demonstrated cost savings, HEIs can use LA to address accountability pressures and transparently demonstrate institutional alignment with public needs (e.g., workforce development) (Selwyn, 2015). Williamson (2016, p. 138) argues that LA is a powerful and distinct form of "digital educational governance" that reimagines the same "data practices of data analysis, visualization, prediction and prescription" used for teaching and learning for administrative purposes and the design of education policy.

Applications of Educational Data Mining and Learning Analytics

Since LA emerged around 2010, HEIs have directed data mining and analytic practices to novel ends in and out of the classroom. Before students even enroll, HEIs create profiles about prospective students based on information students disclose on their interest forms for SAT and ACT surveys, and in their applications for admission (Borden & Coates 2017; Rienties, Cross, & Zdrahal 2017). These profiles include a mixture of demographic, academic, financial, and familial information. Admissions offices then use this and other information to curate an incoming class that takes into account students' calculated "demonstrated interest" in the institution, their probability of enrolling, and modeling that considers how much financial aid is necessary to lure a student to enroll (Lloyd, 2014; McGrath, 2014). While some institutions continue to use traditional methods for recruitment purposes, other institutions are adopting analytic practices informed by interactions with admissions officers and the institution—requests for information, e-mail exchanges, social media "likes," and institutional website clickstreams—that are made into analyzable datapoints (Barnds, 2013).

Tracking and analysis of student life continue after students begin their coursework. Significant research and technological development have focused on predicting student success in a given course and providing instructors tools to intervene when success looks unlikely (Macfadyen & Dawson, 2012). Common learning management systems (LMSs), like Canvas and Blackboard, all have predictive features based on clickstream data, and increasingly LMSs are incorporating advanced affordances that create social network maps to determine students' connections (or lack thereof) with their peers and instructor (Filvà, García-Peñalvo, & Forment, 2014; see Strang, 2016). Some new systems use geolocation data derived from sensors and card swipes to take attendance, while biometric data can inform judgments of in-class student engagement (Alcorn, 2013; Schiller, 2015).

LA informs academic advising as well. With LA affordances, advisors are now able to predict programs and courses in which students may find success (Aguilar, Lonn, & Teasley, 2014). The predictive tools are informed by students' informational profiles and professional interests, which are then compared with similar peers to determine students' compatibility with courses and programs (Kraft-Terry & Kau, 2016). Other affordances of advising analytics take into account markers that determine whether or not a student is ready to pursue a university education and likely to be retained each semester (Phillips, 2013). The use of advising analytics has resulted in notable findings for two institutions in particular. Southern Illinois University's "term-to-term retention for first-time, full-time students rose from 83.1 percent in the 2012–2013 academic year to 86.7 percent the following year," representing nearly one million dollars in recovered tuition (Schaffhauser, 2014). And Georgia State University (GSU), whose predictive model included factors that impede a student's chances of success, increased semester-to-semester retention by five percent, reduced time-to-degree rates, and saved the state's taxpayers nearly five million dollars (Kamenetz, 2016; University Innovation Alliance, n.d.). In contrast to the findings at these insitutions, a multi-institution study of advising analytics found no significant impacts, and it should be noted that impacts—positive or negative—should not be attributed to *just* the use of an analytic tool and may arise due to investments in personnel, other resources, and changes in policy, among other things (Alamuddin, Rossman, & Kurzweil, 2018).

Academic libraries have recently begun to participate in LA initiatives. Much of this work is motivated by a need for librarians to justify their cost expenditures and demonstrate how practices directly impact student learning (Connaway, Harvey, Kitzie, & Mikitish, 2017; Oakleaf, 2010). In one library-based LA study in Australia, the authors aggregated all the data they could obtain within—according to them—ethical, political, and technical boundaries (Jantti & Cox, 2013). Their data included demographic information, academic performance measures, and a mixture of library-related electronic and resource usage data, which they used to correlate library use with academic performance and develop interventions. The library data are accessible by instructors, who use it to infer that low library usage is a proxy for risky academic behavior (Jantti, 2016).

Student Perceptions and Moral Questions

Student Perceptions of LA

Data infrastructures and related practices in support of LA surface significant concerns regarding student surveillance and informational privacy (Heath, 2014). Like privacy issues associated with data mining in other contexts, LA also raise questions regarding individual autonomy and informational controls (Pardo & Siemens, 2014; Rubel & Jones, 2017) in ways that bring to the fore power, fairness, and transparency concerns (Lawson, Beer, Rossi, Moore, & Fleming, 2016). The latter points are especially apropos given the black-boxed (and potentially biased) nature of LA technologies and the increasing reliance by HEIs on vendors who help manage and profit from a glut of student data (Mittelstadt, 2016; Pasquale, 2015; see Johnson, 2019). Given these concerns and others, we are led to ask: What do students think of LA practices and the datafication of their educational experience?

Students have expressed surprise upon learning about LA (Roberts, Howell, Seaman, & Gibson, 2016), and they are concerned, uneasy, and irritated when they learn that HEIs are developing data-driven profiles to build and act on predictive models (Slade & Prinsloo, 2015).[1] Students are willing to share data related to their academic performance, but they are not inclined to share non-academic data, such as their personal information and data trails regarding on- and offline behaviors (datapoints LA proponents find immensely valuable) (Ifenthaler & Schumacher, 2016). Other research on student privacy perceptions signals that students are able to parse data and information flows to make specific privacy arguments regarding access, control, and informed consent (Jones, Perry, Goben, Asher, Briney, Robertshaw, & Salo, 2019). The problem is that students have few legal options and few (if any) technical tools to control representative data and how their university uses such data (Zeide, 2016). Perhaps some students link their discomfort to their lack of knowledge about how, *exactly*, institutions protect their privacy (Fisher, Valenzuela, & Whale, 2014). Several high-profile examples demonstrate how LA practices validate students' anxieties.

[1] Empirical findings to-date are a limited snapshot. While insightful, longitudinal and/or large-scale research would 1) establish whether or not these views are static or dynamic and 2) reveal more nuance.

Opacity and Unfairness: Killing the Bunnies at Mount St. Mary's University

The former president of Mount St. Mary's University (MSMU), Simon Newman, developed a controversial plan to improve retention rates, which is an important metric used by both accreditors and national rankings (Lee, 2016). To improve retention, Newman required incoming students to take a personality survey as part of their first-year seminar. The survey began with the following introduction:

> This year, we are going to start the Veritas Symposium by providing you with a very valuable tool that will help you discover more about yourself. This survey has been developed by a leadership team here at The Mount, and it is based on some of the leading thinking in the area of personal motivation and key factors that determine motivation, success, and happiness. We will ask you some questions about yourself that we would like you to answer as honestly as possible. There are no wrong answers. (Schisler & Golden, 2016, para. 5)

The survey was intended to develop a statistical model for dismissing 20 to 25 at-risk students (Jaschik, 2016, para. 4). When asked about the likelihood of dismissing students who would otherwise go on to be successful, Newman argued that "collateral damage" would occur (Schisler & Golden, 2016, para. 28). Newman stated, "This is hard for you because you think of the students as cuddly bunnies, but you can't. You just have to drown the bunnies… put a Glock to their heads" (Jaschik, 2016, para. 4).

The MSMU survey was implemented in fall 2015, but Newman's scheme to identify and summarily dismiss at-risk students using survey data and the predictive model never manifested. Faculty tasked with generating a list of at-risk students intervened to prevent such an action. Newman's infamous comments were obtained by the student newspaper and published the following semester. Already facing fierce public backlash for his comments, Newman eventually stepped down after pressure from the American Association of University Professors and a vote of no confidence by the MSMU faculty (Prudente, 2016).

The scheme is an egregious example of how the intention behind student data collection and analytics is often opaque and patently unfair. Students and faculty at MSMU were understandably distressed after discovering the ulterior motive driving the Veritas Symposium survey, especially after being misled to think that there were "no wrong [survey] answers." Most LA practices are less conspiratorial, and most HEIs have no trouble justifying why they engage in basic survey practices. Moreover, students have come to *expect* their institutions to collect and analyze representative data to support their educational goals, but those expectations quickly change when they find such practices to be invasive and deceptive (Slade, Prinsloo, & Khalil, 2019).

Precision Surveillance: Tracking Student Movements at the University of Arizona

In 2018, the University of Arizona highlighted work by Professor Sudha Ram, whose research identified at-risk students unlikely to be retained (Blue, 2018). Ram's retention research was "important not only for the obvious reason—that a university's goal is to educate students—but also because retention and graduation rates influence a university's reputation and national rankings" (Blue, 2018, para. 6). While the findings extended research in this area, the methods were what gained significant attention. The three-year study of UoA freshmen was based on student identification card swipes at nearly 700 locations on campus, including among others: the student union, the recreation center, laboratories, libraries, the academic support center, and even when students used their identification to pay for food at vending machines (Blue, 2018). The resulting spatiotemporal data revealed not only students' movements across campus, but they also made visible student-to-student interactions.

The data visualizations showed (in)stability in students' social connections, which the researchers used as factors in the student retention model. Ram (Blue, 2018, para. 15) argues that institutions can take different types of student measurements from the network analysis, such as "the size of their social circle, and... changes in these networks to see if their social circle is shrinking or growing, and if the strength of their connections is increasing or decreasing over time." While the map visualizations were derived from social network analysis, the underlying geolocation data could be used to plot student movements on a campus map. In future studies, UoA aims to include data from 8,000 campus WiFi routers "to get an even more accurate picture of students' movement and behavior" (Blue, 2018, para. 47). While the data used for the study were anonymized, UoA plans to make the data identifiable and available to student advisors to look at in real time (Ehrenkranz, 2018).

LA advocates have long argued that understanding student activities and social interactions could be useful (Parry, 2012). Knowing when and where students connect with their peers opens paths for analysis regarding how students learn outside of traditional classroom environments. Until recently, this was only a *possibility*, not a *reality*. The ubiquity of RFID sensors and single sign-on authentication systems can create precise digital trails that connect individual students to a particular place and time, making it possible to track students' movements and interpersonal relationships in a deeply invasive and granular fashion (Rubel & Jones, 2016).

Body Governance: Faith, Fat, and Fitness Scoring at Oral Roberts University

Oral Roberts University (ORU) is no stranger to controversy surrounding the methods it uses to monitor its students. In the mid-1970s, students were required to participate in a mandatory "Pounds Off Program" which administered skinfold and other obesity tests. Men with more than 25 percent body fat and women with more than 35 percent body fat were forced to "sign a contract promising that they would lose weight...or face suspension and possibly expulsion from the university" (Root, 2015, p. 160). Overweight students were fed specific meals. First year students were required to take fitness courses and maintain a log of their physical activity which informed their earned grades (Root, 2016, para. 12). The Pounds Off Program was quickly disbanded after former students working with the ACLU sued the institution for discrimination.

In 2015, ORU implemented a similar fitness program that has so far resisted legal scrutiny. Students were required to enroll in physical fitness courses, wear FitBit fitness trackers, and take a minimum of 10,000 steps per day and be within "60 to 80 percent of their range for heart rate" over an unspecified amount of time (Chuck, 2016, para. 6). The wearable's data were imported into Desire2Learn, ORU's learning management system, to help instructors analyze students' health and assess students' physical activity. At the time of the announcement, the learning management system excluded collecting geolocation data from the device—though one could imagine the ease at which ORU could toggle such data collection.

Like the UoA revelations, collecting geolocation data could easily unmask a student's social networks and frequent personal associations. When geolocation and demographic data are combined with timestamps and heart-rate data, there exists an opportunity to easily unmask a student's intimate behaviors. At the risk of expulsion, students pledge to not participate in premarital and other "elicit unscriptural" sexual acts (i.e., students in LGBTQ+ sexual relationships) (Oral Roberts University, 2016). Even though a FitBit seems like an innocuous device, the downstream uses of the data it produces can be consequential. Students' physical lives and intimate relationships can become the target of biopolitics and institutional governance (Foucault, 1990; Williamson, 2017).

Justifying Learning Analytics in Higher Education

The Relevance Condition

So far, we have provided an overview of some key features of LA and related practices, and we have described several examples of HEIs using student data and predictive analytics in specious ways. Our task in this section is to understand when it is justifiable to collect, analyze, and use student data in the context of higher education. Our argument is as follows. First, it is not enough that student data be relevant to higher education goals for HEIs to collect, analyze, and use those data for LA. Rather, second, HEIs have a responsibility to engage in LA according to a plan which is itself justifiable. Third, whether a plan is justifiable depends on whether it comports with the values that underwrite higher education in the first place. And, finally, any plan that comports with the values underwriting higher education will treat HEIs as *information fiduciaries* (Balkin, 2016).

Proponents of LA often maintain that collecting and analyzing student data is justifiable so long as it is plausibly relevant to institutions' educational mission. Rubel and Jones (2016) argue that this "relevance condition" is not enough to justify data collection. The gist of that argument is that one cannot tell *a priori* whether information is relevant to learning; therefore, the relevance condition would allow for the inclusion of *any* data for educational data mining practices. Surely there are some sorts of information that should be off-limits. There will be a dispute about what exactly those limits are, but absent any limits, even wholesale collection of data about students' religious and political activities, sex lives, anxieties, and so forth would be permissible. Put another way, the relevance condition would entail that comprehensive, all-inclusive information gathering by HEIs would be permissible.

Moving Beyond Relevance

Our second claim is that whether any particular LA regime is justifiable requires that it be part of a plan, rather than collected pell-mell. This claim follows straightaway from the claim that mere relevance is insufficient justification for data collection and analysis. Data collected and analyzed *just because*, or just because they are available, has no rationale; it is the very model of information collected on the grounds that it may turn out to be relevant. In other words, any data collected without a plan are collected with the mere hope that they will be relevant to the higher education enterprise.

The mere existence of a plan, though, will be insufficient to justify data collection and analysis. There are two other requirements. The first is that the plan must be epistemically sound.

Poorly conceived and designed plans may fail to account for social and historical factors that structure student actions, and they may serve to reify and reinforce those structures. Second, the plan must include institutional support that can effectively use its analytics. Consider the Georgia State case, which is widely touted as an LA success. In addition to collecting and analyzing student data, GSU hired dozens of new advisors and substantially increased student advising opportunities (Ekowo and Palmer 2016). In other words, the success of the program is rooted in having a system that connects with a robust, well-staffed, and professional advising team that can work with students. Absent similar processes and systems for advising, program design, pedagogy, and so forth, data collection and planning will not be effective, and it will not be justifiable.[2]

The Values of Higher Education

The first two claims establish that there are some conditions necessary to morally justify higher education LA beyond relevance and legality. But that leaves open what those conditions are. Hence, our third claim is that a plan is justified only if it comports with the values underwriting higher education in the first place. There is only limited philosophical work on the underlying justifications for higher education. Nonetheless, there are several key values that predominant views agree on. First, higher education should promote wide, integrative understandings of the world and communities. Second, it should promote the freedom of students and others. Third, it should promote fair terms of association within a broad community. Any LA plan should similarly comport with those aims. To see why those are foundational values, consider the following views.

Amy Gutmann (2015, p. 6) recognizes the appeal of the economic case for undergraduate education (for most graduates, college will provide financial benefits that outweigh expenses, and this trend will likely continue), but points out that whether economic payoff does any kind of justificatory work simply assumes the value of economic payoff. Instead, she outlines three key elements, corresponding to who undergraduate education serves, the intellectual goals of undergraduate education, and the community role of higher education. Her first aim is that higher education should provide opportunities on the basis of talent and work (rather than, e.g., birth and wealth). Second is that higher education should aim at "greater integration of knowledge…within the liberal arts and sciences [and] between liberal arts and professional education" (Gutmann, 2015, p. 8). She refers to this as creative understanding. Third, undergraduate education should foster community engagement and contribution based on their creative understandings. Derek Bok (2006) offers a compatible view, which rejects the idea of a unique purpose of higher education. Instead, his multifaceted perspective endorses communication, critical thinking, citizenship, living with diversity, living in a more global society, and employment as valuable goals (Bok, 2006, pp. 67–81).

Others claim that the foundations of higher education are informed by demands of liberal, democratic society. Chris Bertram (2015) explains that the range of reasons that at least prima facie meet liberal justificatory burdens include "expanding the well-being, opportunities, and freedoms of citizens." (p. 33). They also include the "associative needs of democratic polities," that is, the broad understandings, knowledge, and abilities necessary to engage in the social and collaborative democratic process. And providing individuals with exposures, discussions, and understandings of the world and conceptual tools necessary to understand theirs and others' ways

[2] We thank our anonymous reviewer for this point.

of living. To do so, in part, requires HEIs to incorporate conceptions of justice, provide remedies, and even model justice (Fullinwinder & Lichtenberg, 2015; Kelly, 2015). In summary, the interests that citizens have in understanding, forming, and revising their conceptions of the good can be a permissible reason justifying higher education in liberal democracies. HEIs, then, should act as an exemplar of the kinds of social structures that, if reflected in society overall, would meet (or at least track) demands of justice.

Higher Education Institutions as Information Fiduciaries

Student Trust

Our argument for understanding HEIs as information fiduciaries starts from the standpoint of the relationship between students and their HEIs. It is an open question as to why students should trust their institutions to use representative data to serve their interests, especially when emerging practices seem to break existing privacy norms. The benefits from these data-driven surveillance practices do not necessarily redound to the individual student experiencing the surveillance. In fact, it seems that the balance of benefits leans heavily toward HEIs, especially where financial savings are considered. Additionally, the opacity around educational data mining also validates students' unease. They are not informed when, how, by whom, and why they are being surveilled. And the latter part is especially important as non-human actors become prominent in LA technologies. As algorithms and artificial intelligence become mature, it is increasingly likely that humans will not oversee automated technologies doing the surveilling and the actions they take (Prinsloo, 2017).

Students will become more aware of LA practices and the potential harm as they become more common in the educational experience, but if HEIs remain silent about their data practices, it is plausible that students will change their actions to game data analytics system or chill their behavior out of fear. Student perceptions research suggests that individuals are already changing their behaviors or are will willing do so in response to knowledge of LA and other data mining practices (Jones et al., 2019). If students choose to suppress their educational and personal interests, then LA will effectively limit intellectual freedom and conflict with higher education's larger mission to develop an educated, free-thinking citizenry.

Students expect their institutions to take care of the data and information they disclose, to use it in appropriate ways. Here, appropriateness generally means that the information is carefully stewarded and used in loyalty to the student, which positively engenders trust. But if, for instance, an HEI uses privately disclosed student information to gain advantages (e.g., social, political, financial), the institution would fail its responsibility to its primary stakeholders: its students. These are the hallmarks of fiduciary duties, and this moves toward a claim that HEIs should be considered what Jack Balkin (2016) calls "information fiduciaries."

Information Fiduciaries and Socially Important Relationships

In "Information Fiduciaries and the First Amendment," Balkin (2016) seeks to address the longstanding conflict between the values of information privacy and free speech. That conflict, in summary, is that the widespread collection, analysis, and use of data affects many aspects of people's lives, and that gives rise to concerns for individual privacy. However, any restriction on using and sharing such information would restrict a form of speech. Hence, two deeply held values are at odds. However, in the U.S. there are innumerable ways in which speech is legitimately restricted consistent with the First Amendment. Balkin's task is to draw on existing legal structures in order to argue that at least some entities have duties to protect others' information, and have a *legal* obligation to fulfill those duties consistent with the First Amendment, even if it is a limit on speech. So, even "absent an express promise not to reveal, use, or sell information [such as in contracts], *there is a duty not to do so* [emphasis added]" (Balkin, 2016, p. 1206).

Balkin's argument is a novel contrast with most U.S. privacy law, which is domain-specific. There are privacy protections for health information (HIPAA, GINA), education (FERPA), foreign intelligence (FISA), criminal investigation (Fourth Amendment, Title III), and so forth. Balkin, though, wishes to change that understanding to one that focuses on *relationships* instead of domains. Specifically, he argues that certain kinds of relationships create fiduciary responsibilities surrounding data. This is akin to the fiduciary responsibilities that various professions (e.g., medical, legal, and—until recently—financial professionals) have to act in the best interests of clients. He calls these *information fiduciaries*:

> Because of their special power over others and their special relationships to others, information fiduciaries have special duties to act in ways that do not harm the interests of the people whose information they collect, analyze, use, sell, and distribute. These duties place them in a different position from other businesses and people who obtain and use digital information. And because of their different position, the First Amendment permits somewhat greater regulation of information fiduciaries than it does for other people and entities. (Balkin, 2016, p. 1186)

Consider lawyers and physicians. Each is a profession that holds itself out as worthy of client trust. Lawyers assume that clients give them sufficient, often extremely sensitive information so that they may provide the best legal representation possible, and hence rely on the fact that clients trust them with that information. Moreover, clients must trust both that lawyers will not disclose sensitive information and that lawyers will act in their best interests (for example, not representing parties with divergent interests or having financial stakes that run counter to the client's). Physicians need patients to disclose comprehensive and accurate information to receive treatment, all of which requires patients to trust that their medical caregivers will protect their information. These relationships are socially important enough, and the professions themselves trust-dependent enough, that they have both moral and legal responsibilities to act not as mere business clients, but as fiduciaries. That is, to act in the best interests of the clients.

Balkin's argument is that the important features underwriting lawyers' and physicians' fiduciary responsibilities to clients and patients also exist in other relationships, specifically relationships between entities collecting, analyzing, and using personal data. Just as lawyers and physicians hold themselves out as responsible professionals so that their clients and patients trust them with information, cases, and healthcare, businesses hold themselves out as responsible entities so that others share data.

Moreover, the same values underwriting fiduciary relationships in law, medicine, and elsewhere are applicable in the context of information collection, analysis, and use. Specifically, each involves people who are vulnerable (people in litigation, people seeking treatment, people sharing personal data), thus are in a deeply *dependent* relationship. Just as we depend on lawyers to marshal litigation, transactions, estates, and divorces, we depend on data-businesses to communicate and seek information. It is exceedingly difficult to navigate our most important social and information needs without them being mediated by companies that make money from our data.

Like lawyers and doctors, data-driven organizations and companies *hold themselves out as experts* in various domains: “For example, online dating services tell us they will match us with potential partners, online transportation services say they will match us with cars, search engines purport to give us the information we need quickly and efficiently, and so on” (Balkin, 2016, p. 1222). Another key similarity is that such companies know that the data they hold is valuable (indeed, it is often the basis of their business models) and that it is particularly vulnerable. Because of these similarities, people would reasonably seek reassurance that the entities with whom they share personal information will act responsibly and in ways that do not put them at a disadvantage.

Based on these key values, Balkin argues that people and businesses act as information fiduciaries when the following conditions are true:

1. They hold themselves out to the public as privacy-respecting organizations in order to gain trust.
2. They give individuals reason to believe that they will not disclose or misuse their information.
3. Individuals reasonably believe that these people or entities will not disclose or misuse their personal information based on existing social norms of reasonable behavior, existing patterns of practice, or other objective factors that reasonably justify their trust (Balkin, 2016, p. 1223–24, citing *Restatement of Data Privacy Principles* §5.2).

HEIs would certainly appear to fulfill each of the aforementioned criteria, and hence are information fiduciaries on Balkin’s account. Our argument is that Balkin’s framework identifies the importance of trusting relationships and their intersection with student data and information. And as the cases below demonstrate, there are notable instances when HEIs do not fulfill their information fiduciary responsibilities.

Data Practices at Variance with Information Fiduciary Responsibilities

FERPA and Third Parties

While FERPA would ostensibly govern how HEIs manage student information, Elana Zeide (2016, pp. 358–359) notes that in practice FERPA has created a structure in which HEIs have “almost complete authority over data collection, security, use, and retention.” HEIs determine what is of “legitimate educational interest” and enjoy incredible leverage in deciding what data are protected by FERPA and what are not. Sometimes what is legitimate need not even be educational in scope, as long as HEIs can justify their actions. As Nancy Tribbensee (2008, p. 400) writes, “A legitimate educational interest is not strictly limited to academic or educational matters, and permitted disclosures are not limited to those that may address the student’s interest or that may be to the benefit of the student.” In defining a legitimate educational interest liberally, it opens up the opportunity for data to flow more freely to so-called “school officials.”

In 2008, the Department of Education restructured FERPA to give more leverage to private companies by expanding the definition of “school officials,” (Family Educational Rights and Privacy, Proposed Rule). Under the new rule, HEIs can disclose student data to “contractor[s], consultant[s], volunteer[s], and other part[ies]” who “[perform] an institutional service or function for which the school… would otherwise use its own employees” (Privacy Technical Assistance Center, 2014; Family Educational Rights and Privacy, Proposed Rule). As a consequence, third-party “school officials” can now use student data and information in the course of providing HEIs services to design new products or reach students with targeted messaging and advertisements. If the third-party provider is using student data in a way that serves the purpose for which it was originally disclosed, their use is not prohibited by FERPA (Privacy Technical Assistance Center, 2014).

Pearson’s “social-psychological” messaging is a particularly good demonstration of FERPA’s weaknesses and, as well, the need for HEIs to attend to their higher responsibilities as information fiduciaries. In April of 2018, Pearson ran an experiment on over 9,000 students at 165 United States HEIs who were using its MyLab Programming application (Herold, 2018). The parallels between the Pearson study and the Facebook emotional contagion study are striking: A private company conducted manipulative research on unknowing participants, who were neither made aware of the project nor consented to it, for their own gain (see Selinger & Hartzog, 2015). HEIs were “randomly assigned [...] to use different versions of that software, tracking whether students who received [different messaging] attempted and completed more problems than their counterparts at other institutions” (Herold, 2018, para. 3). Regardless of the goals and the outcomes, Pearson effectively treated students like research subjects by providing differential incentives that impacted student learning outcomes. All of this was accomplished without any institutional oversight and completely within the legal boundaries set by FERPA.

The Pearson case highlights the need to hold HEIs to information fiduciary standards. Students expect fair treatment and opportunities in the classroom. They trust that their instructors, and by extension, their institution as a whole will use representative data and information as a means to develop a just educational system. Enabling third parties, unwittingly or knowingly, to use student data to do the opposite breaks this expectation. Perhaps a larger issue is that research institutions generally model ethical research. Legally, they are required to abide by FDA regulations for human subjects research. Students are to varying degrees aware that institutions put in place institutional review boards (IRBs) to maintain high ethical standards. But when an institution enables a third-party educational technology company to bypass research ethics checks and deny students their legal rights (here as human subjects), these practices disrespect the trust students place in their educational institutions.

eTexts and Data Sales

The LMS is the locus of behavioral data gathering due to its central position in teaching and learning. It is at the same time the source of educational objects (e.g., lectures, readings, quizzes) and the place in which students and instructors (electronically) gather to discuss and engage those same objects. With learning tools interoperability (LTI) standards, LMSs are also the hub from which spokes of other educational technologies extend. Because of the widespread adoption of LTI in common LMSs, students have increased access to eTexts (or eBooks). Like LMSs, eText systems capture student behaviors in data. Instructors gain access to analytics describing when and for how long students engage eTexts, along with what pages they interact with (a proxy for reading). Some eText systems with commenting affordances provide opportunities to create social network analyses of student interactions.

The use of eTexts embedded in LMSs could produce benefits for both students and instructors. Institutions pursue eText integrations into LMSs because of the cost savings to students. Physical textbooks are financially burdensome, whereas eTexts are reportedly a fraction of the cost to rent (Abaci, Quick, & Morrone, 2017). For instance, at Indiana University, "4,595 students in 136 unique course sections used 152 different e-text titles, which resulted in their saving $559,347 in textbook costs" (Abaci, Morrone, & Dennis, 2015, para. 9). And with eTexts, the learning environment provides instructors new opportunities to engage students in close reading and assess student progress accordingly. That said, evidence exists that even though eTexts present an affordable option, there are a number of issues to consider. First, students prefer print texts and are more likely than not to buy a low-cost print version of a text *even when* a digital version is freely available (see Bossaller & Kammer, 2014). Second, eTexts may reduce some costs but create other financial hurdles by requiring students to own (or otherwise have easy access to) devices and reliable Internet. Finally, some HEI policies *force* students to purchase eTexts or enroll in an alternative course sometimes over a month before courses even begin (see Indiana University, n.d.), which is an undue burden.

eTexts are justified insofar that they enhance teaching and learning practices. When eText initiatives are supported by robust institutional support for, say, adopting effective pedagogies and evolving digital environments to enable peer-to-peer learning, then data collection and analysis of student reading behaviors hurdles one moral requirement. However, if HEIs pursue eTexts primarily for the financial gains, and if such practices open up students to other possible harms, then the plan is not justified and fails to account for larger information fiduciary responsibilities. Unizin provides an example of failing to meet such responsibilities.

Unizin enables their institutional partners and their respective students access to eTexts through its Engage platform. With McGraw-Hill Education, Pearson, Cengage, and other publishers, Unizin loads the eText content into Engage at reduced rates. In return, the publishers gain access to learner data captured by Engage, which are deposited in the UDP and are standardized using the UCDM. With some publishers, Unizin collaborates on LA initiatives (Reed & Pearsall, 2018). Some eText data will plausibly contain substantive student work in the form of text comments, annotations, and collaborative writings. For sure, the data will capture reading behaviors in addition to whatever metadata are associated with eText interactions.

Unizin's UDP data aggregation model raises the issue that companies, researchers and other third parties *not* affiliated with a student's institution will gain access to these data and use them for their own benefit. Turnitin represents one model of potential harm. The plagiarism detection company amassed a substantial database of student essays and other artifacts that had been submitted for plagiarism analysis since 1998. In 2019, the company was purchased by media conglomerate Advance Publications for $1.75 billion, representing a deal "larger than the total amount that edtech startups raised in 2018" (Johnson, 2019, para. 8). It is plausible that publishers sell data generated in eText systems among themselves or to major data brokers, like Acxiom and Experian. Similarly, eText and other data stored in Unizin's UDP provide an opportunity for the consortium to sell data or provide limited subscriptions to companies seeking access to large stores of student data to develop products and services, turning the data warehouse into a source of revenue for the institutions it represents. These actions may support the financial interests of institutions and those with whom they conduct business, but they neither directly benefit the students they represent nor fulfill their information fiduciary responsibilities.

Advisors

Advisors use descriptive statistics and predictive models to understand students' personal and academic profiles, as well as forecast courses and programs of study in which they will likely be successful (Aguilar, Lonn, & Teasley, 2014; Kraft-Terry & Kau, 2016). Using these systems may prove helpful for students by opening up educational pathways about which they were previously unaware. And it may also be the case that they enable students to more skillfully navigate complex curricula designs in ways that reduce poor course choices and decrease the amount of time it takes students to earn their degree. Systems can nudge students to seek the support of advisors in times of need using just-in-time messaging strategies. As previously discussed, institutions have seen retention increases, reduced time-to-degree rates, and financial savings from advising analytics; some of these things have directly benefited under-represented student populations, many of whom often lack the support they need to finish their degree (Ekowo & Palmer, 2016; Hefling, 2019).

Students make advising appointments to discuss personal issues and develop strategies to achieve greater academic success. As such, these exchanges can be deeply personal, and they expose a student to influence. Advisors have a professional responsibility in these meetings to guide students toward resources and engage in reflective dialogue; moreover, these meetings provide students the space to construct their own definitions of success and set their academic goals (Harrell & Holcroft, 2012). But LA technologies and political pressures motivating their adoption raise a notable conflict of interest.

HEIs may put their advisors in a situation where the advice they suggest and the interventions they develop are driven more by predictive measures and less by student needs. So, it is plausible that advisors may contravene students' interests and take advantage of their vulnerability. This could materialize because of a couple of reasons. First, institutions may see the predictions as more effective than an advisor's abilities, and force advisors to privilege the predictions over their honed intuition and professional best practices; some evidence of this exists (see Jones, 2019). Second, even if advisor expertise is still supported, the pressure to use data-driven insights and demonstrate to outside stakeholders the use thereof may override the guidance advisors could provide to students. About this, Jones (2019) writes:

> We can understand "personalized" education as being less about the needs of the learners and more about serving the interests of higher education institutions—namely improving profits and their position with accountability hawks—by surfacing analyzable data for the purposes of demonstrating politically prudent outcomes. (p. 453)

Third, HEIs may push students into courses and programs where students are predicted to succeed. In this case, students' personal information is used to develop such predictions (i.e., their privacy is invaded) and the ability to make informed decisions according to their own interests is limited (i.e., their autonomy is reduced). In all cases, advisors use LA insights derived from student data and information in ways that support institutional interests, not the interests of students.

Conclusion

This article discussed educational data mining (generally) and LA (specifically) with regard to related practices, goals, and moral issues. We argued that emerging data mining and analytic practices, which include expansive data sharing within and outside of institutional boundaries, raise significant concerns regarding the trust students place in their institutions to use that data according to their expectations. Using Jack Balkin's (2016) information fiduciary concept, we asserted that HEIs have special obligations to use data and information about students when related practices 1) advance student interests, 2) support the educational mission of the institution, 3) use data only when doing so is consistent with principles of intellectual freedom, and 4) use data only in a way that is consistent with profound trust between student and institution.

The article addresses the strong belief that HEIs have a moral obligation to act in students' interests, and that LA surfaces such an obligation in ways other sociotechnical systems have not. But our argument bends this obligation in a different direction. Prinsloo and Slade's (2017) view of HEI fiduciary responsibilities suggests that the growth of data collection is without limits; therefore, "the necessity and scope of [a HEI's] obligation to act" on data increases. To not act on all available data, especially when a student is identified as "more likely to fail, but not warned or supported," suggests that HEIs are not fulfilling their educational mandate. Furthermore, their position is motivated by a concern that not acting on data is increasingly implausible given financial and social pressures on HEIs, and that failing to use data when predictions suggest student failure puts them in legal jeopardy. In contrast, we argue that an institution's fiduciary responsibility requires *limited* data collection and analysis, and that such data practices should *only* be pursued when they align with and are directed to support student interests and protect their privacy.

Some readers may contend that the obligation to fulfill information fiduciary responsibilities will change depending on a number of factors, including the type of data practice and the role of the institutional actor, among other things. It is accurate to state that our focus has been at the institutional level, and we have not attended to these fine-grained aspects. Although we believe that all institutional actors should be guided in their work by their information fiduciary responsibility, how this looks in practice and is embedded in policy needs further work. We encourage others to contribute to the higher education information fiduciary concept by taking up this approach.

The high-profile examples at MSMU, UoA, and ORU, along with the descriptions of common data practices, clearly indicate how the pursuit and application of LA methods, tools, and infrastructures can create conflicts of interests between institutions and their students. Moreover, these cases show how particularly egregious invasions of student privacy provide students valid reasons to be distrustful of their universities. Moving forward, universities should reflect on their information fiduciary responsibility and use their fiduciary duty to guide their LA practices and the development of related policy.

Acknowledgments

The authors thank those who provided feedback on presentations of this work at the 2018 Information Ethics Roundtable held in Copenhagen, Denmark and the 2018 Amsterdam Privacy Conference.

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