Learning Analytics and the Academic Library: Professional Ethics Commitments at a Crossroads

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Abstract

In this paper, the authors address learning analytics and the ways academic libraries are beginning to participate in wider institutional learning analytics initiatives. Since there are moral issues associated with learning analytics, the authors consider how data mining practices run counter to ethical principles in the American Library Association's "Code of Ethics." Specifically, the authors address how learning analytics implicates professional commitments to promote intellectual freedom; protect patron privacy and confidentiality; and balance intellectual property interests between library users, their institution, and content creators and vendors. The authors recommend that librarians should embed their ethical positions in technological designs, practices, and governance mechanisms.

Keywords: learning analytics, data mining, Big Data, higher education, professional ethics, information privacy, intellectual freedom, intellectual property

Learning analytics and the academic library: Professional ethics commitments at a crossroads

"We cannot allow our ethical principles to stand as mere monoliths…. That our values pose ethical dilemmas for us in practice is a good thing and should be welcomed by us: from debating such dilemmas comes strength of mission."

David McMenemy[1]

1. Introduction

Higher education institutions (HEIs) are aggregating and analyzing student data, information, and the digital trails they leave in information systems to better understand student behaviors. Among other things, these data-driven insights hold the potential to cast light into the black box of learning and student life. The primary aim is to use data analytics to help HEIs address urgent concerns related to low retention rates and extended time-to-degree measures, which can then improve on the efficiency and effectiveness of institutional practices.

Educational data mining employs Big Data methods; in doing so, it also elicits Big Data's band of problems. Big Data uncovers personally identifiable information and flows that information to a variety of different actors. But it is problematic that these new flows are opaque to the individuals they represent, yet hold significant influence in their lives. Rising to the top are complicated and troubling issues about informational privacy, transparency, personal autonomy, and other questions of what is morally acceptable. The question, then, is how to ethically pursue the benefits of educational data mining while accounting for the potential harms.

Ethical practice is often supported by codified principles, and researchers have constructed broad codes of ethics to minimize harms to students.[2] Similarly, a few HEIs have developed campus-wide policies.[3, 4] While institutions may feel justified and morally at ease in pursuing the benefits of educational data mining, their interests and practices may lead to "unintended consequences and perverse incentives" to analyze sensitive student data in ways that harm students and conflict with ethical commitments made by professional communities, such as librarians.[5, 6]

In this paper, we address learning analytics (LA)–a form of educational data mining–and the ways academic libraries are beginning to create capacity for LA or participate in wider institutional LA initiatives. Since there are moral issues associated with LA, we consider how data mining practices run counter to ethical principles in the American Library Association's "Code of Ethics." Specifically, we address how LA implicates professional commitments to promote intellectual freedom; protect patron privacy and confidentiality; and balance intellectual property interests between library users, their institution, and content creators and vendors.

We make three arguments aligned to these three ethical commitments. First, it is plausible that LA negatively affects the conditions necessary for the free pursuit and dissemination of ideas by tracking and influencing intellectual behaviors. Second, LA is by design a surveillance technology, and it can opaquely pry into students' privacy without empowering student choice over information flows. Third, the ability to surveil students also allows institutions and content vendors to expand the use of digital rights management technologies; moreover, it creates conditions where institutions and content vendors may use student data as a bartering chip in contract negotiations.

We end the paper by positing that librarians have a professional responsibility to reflect on and advocate for their ethical positions when participating in LA. If LA matures further, librarians' ethical commitments may be challenged by institutional actors who do not share their professional values. We recommend that librarians advocate for their ethical positions within and outside the boundaries of their institution, participate in data governance practices to embed their values in information flows, and work closely with policy-makers to design policies in ways that consider their professional ethics.

2. Big Data and Learning Analytics

2.1. An understanding of Big Data

Learning analytics (LA) is a type of Big Data practice. After boyd and Crawford, we capitalize "Big Data" to highlight it as a cultural, technological, and scholarly phenomenon, a "paradigm rather than a particular technology."[7, 8] Defining Big Data as a socio-technical phenomenon fruitfully moves the conversation away from techno-centric and myopic definitions of Big Data.[9]

Big Data practices significantly differ from the flows of information currently considered the norm in scholarly research and assessment. Current research practices, often called "small data," involve actors developing and curating limited datasets in order to answer preset and particular questions.[10] Smaller datasets and related practices generally respect informational norms, or expectations of information flow, because actors seek consent for data gathering beforehand and use the data as means to explicitly agreed upon and respected ends.[11, 12]

The Big Data ethos, however, motivates actors to develop boundless datasets to be used in ways that are often unanticipated at time of collection. Individuals, organizations, and institutions implementing Big Data initiatives argue that taking an "n = all" approach and

aggregating all the data they can get will optimize their data-driven projects.[13, 14] Immense

datasets, made possible by aggregating and intertwining disparate and diverse sources of data, no

longer require painstaking curation of scientific, statistically powerful samples. Instead, data

scientists can conduct "fishing expeditions… to look hard for patterns and report any

comparisons that happen to be statistically significant."[15]

2.2. Learning analytics as a Big Data practice

LA is commonly defined as the "measurement, collection, analysis and reporting of data

about learners and their contexts, for purposes of understanding and optimizing learning and the

environments in which it occurs."[16] To maximize LA's potential, HEIs implementing LA are

working to "de-silo"[17] so-called "static data" about and created by students stored in

departmental offices across campus by building up institution-wide data warehouses[18, 19, 20] to

capture "fluid data."[21, 22] Shacklock explains the difference between static and fluid data this

way:

> Static data is that which is collected, recorded and stored by institutions [including]
>
> student records, staff data, financial data and estates data. Fluid data […] is generated
>
> through the increasingly digital way a student interacts with their university, such as card
>
> swipe data from access-controlled campus buildings, log-ins to the virtual learning
>
> environment (VLE) and e-books or online journal downloads.[23]

Tightly-guarded information and technically inaccessible data hinders LA's efficacy.

Ubiquitous campus educational, professional, and personal information systems store a

significant amount of data and information created by or about students. Data captures begin

even before a student applies for admission and extend to alumni status, enabling colleges and

universities to probe student behaviors as a snapshot or over time.[24, 25] Students are easily

accessible data subjects, and HEIs can avoid seeking student consent for data collection,

retaining and analyzing student data with impunity because the data is generated as part of the

educational process.[26] Emerging troves of student data can be enlarged by capturing the

metadata, known as "data exhaust"[27] or "digital footprints"[28] students leave as they interact with

information systems.

2.3. Motivations driving LA

HEIs deploy LA to understand student behaviors within learning contexts and optimize

learning environments. Examining student data may directly or only tangentially benefit

students, however, or may benefit only the institution itself. Goals tangential to student

achievement include resource optimization and revenue increases.[29, 30, 31] HEIs often believe that

LA will unveil hidden cost savings and streamline operational practices.[32] Improved fiscal

management may enable HEIs to defend themselves against accountability calls and measures

due to ongoing tuition increases and the rise in student loan debt.[33, 34]

Beyond its business intelligence aspects, LA initiatives focus on directly improving

student learning experiences.[35] Advocates of LA argue that analyzing the emerging trove of

student data will finally unpack the "black box" of learning, enabling better comprehension of

inputs and outputs relevant to successful learning experiences.[36, 37, 38] Specifically, proponents of

data-driven education argue that datifying the learning experience will create actionable insights

into student success and failure, and predictive algorithms built on large datasets will provide

HEIs the tools to determine students' future educational progress.[39]

2.4. Applications of learning analytics

Because data on prospective students is valuable to HEIs well before enrollment, admissions departments are developing troves of data and analytic capacities in novel ways. Some of this information comes from standard sources, such as ACT and SAT scores, which admissions departments purchase en masse to micro-target prospective students.[40] These same admissions officers are also mining data from social media,[41, 42] looking at how prospective students interact with their institution's website,[43] and consulting with outside analytics companies.[44] HEIs argue that the more they know about their potential incoming class, the more informed and effective their admissions decisions will be.[45] Comprehensive data about prospective students can help HEIs understand the level of a given student's interest, the probability that she will apply *and* enroll, and whether past personal information and academic performance predict her chances of future success and graduation while enrolled.

Once students enroll, institutions gather data on "engagement" hoping to retain them. Whether a student is participating in campus life has historically been difficult to measure, but campus mobile applications can log interactions to track what students are interested in and need help with, or whether they have lost contact with campus.[46] HEIs can also examine RFID-embedded student IDs and swipe card activity to learn what campus services and events they are participating in and when.[47] Similarly, campuses such as Northern Arizona University have moved to automate attendance tracking via RFID technologies, arguing that attendance correlates with higher academic achievement.[48] Some universities automatically notify a student's advisor when an attendance system records multiple absences.[49, 50] Others like Class120 use mobile applications' geolocation ability to create "digital fences" around classroom areas. When

students are not inside the fence when the class is in session, the system marks them absent and

can alert institutional representatives–or even the students' parents.[51]

Advising is a key variable in student academic achievement,[52] so matching students with

the most appropriate academic path is often a driving goal for LA initiatives. HEIs have turned to

eAdvising systems that use Big Data tools and techniques to analyze student profiles, predict a

student's chances of success, and suggest interventions to keep them on track to graduation.

Systems like Degree Compass consider a student's selected major and their achievement in past

courses, comparing that achievement with similar peers.[53] The system then nudges students to

enroll in particular classes that "will best help undergraduates move through their programs of

study most successfully—and most expeditiously."[54] Other systems penalize students for not

making adequate progress on their degree or enrolling in courses not recommended to them.[55]

Repercussions include forcing students to meet with advisors or choose a new major.

Learning management systems (LMSs), where instructors facilitate online learning

experiences for distance and on-campus students alike, often include relatively mature LA

technology. These spaces capture metadata related to system ingress and egress and student

interactions with peers and learning objects, in addition to content students create and grades

they earn. LA tools like Course Signals or Desire2Learn's Insights measure student progress and

peer engagement via social network graphs, and from these data try to identify at-risk students.

Purdue University's institutional research on their implementation of Course Signals found that it

improved retention, graduation rates, and grades.[56] Although, some have called into question the

statistical validity of the university's findings.[57, 58, 59]

Some institutions and researchers seek to augment learner data in LMSs with biometric

and other sensor data from fitness trackers. Oral Roberts University now pressures its incoming

classes to purchase Fitbits, arguing that measuring student movement is part and parcel of fulfilling the institution's mission of educating the mind as well as the body and spirit.[60] Step and heart-rate data from the Fitbits are automatically sent to the LMS and graded, but grades are lowered if they opt out.[61] Similarly, the Bill and Melinda Gates Foundation has funded $1.4 million in research to build and develop a so-called "engagement pedometer," which uses galvanic skin response sensors to inform instructors in "real-time 'which kids are tuned in and which are zoned out.'"[62, 63] In the same vein, emerging research is adapting facial recognition software to manage attendance-taking in large classrooms and determine how engaged students are in lessons by analyzing facial movements.[64, 65] Other research used passive sensors from mobile phones to infer social and study behaviors by analyzing conversations and GPS-plotted movements.[66] The data was then correlated with grade point averages to determine what kind of behaviors related to higher grade outcomes.

Analytics from emerging flows of student information are usually accessible to institutional actors (e.g., instructors, advisors, and administrators) only, though some proponents of LA argue that enabling students to view their data dashboards could reap benefits. Couched in terms of the quantified-self movement, researchers argue that visualizing learning progress and behaviors can improve student decisions, motivate them, and enhance their autonomy as well as enabling them to set goals and see how behavior changes affect learning outcomes.[67, 68] LA tools like Purdue University's "Pattern" mobile application are beginning to integrate graphs and metrics to inform students of their progress and how they compare with their peers. To date, the level of access a student has to data and analytics about herself is still low, but access by institutional actors is high.

3. Academic Libraries, Learning Analytics, and Ethical Challenges

3.1. Academic libraries and learning analytics

Academic libraries have rigorously evaluated their services and collections with quantitative and qualitative methods for decades. More recently, some libraries have built LA capacity to analyze student behaviors in library information systems, often to attest to a library's value with respect to student learning outcomes.[69] Research projects have begun to consider the relationship between library services and grades, retention, and achievement, representing a "significant turn" in assessment and evaluation.[70, 71, 72, 73, 74, 75] The shift from studying student experience in libraries to student achievement reflects contemporary pressures on HEIs, according to the Association of College and Research Libraries.[76] Its report stresses that libraries are under increased scrutiny by institutional accreditors and other stakeholders to prove that library practices are aligned with institutional needs and effect positive learning outcomes.

Duderstadt argues that "the university library may be the most important observation post for studying how students really learn," such that joining datasets within and outside of the library will be key to discovering the impact of library services and spaces on student learning.[77] While libraries and library researchers have pursued data mining for niche projects,[78, 79, 80] larger-scale, Big Data-style mining has proven difficult until libraries began working with other campus departments to develop data warehouses and analytic capacity.[81, 82] For instance, Jantti and Cox joined "as many datasets as ethically, politically, and technically possible," mirroring the Big Data ethos motivating many LA initiatives.[83]

The Huddersfield University (HU) Library Impact Data Project (LIDP) sought a correlation between library activity data and degree attainment.[84, 85] Researchers analyzed circulation data from the university's integrated library system, eResource access, and student entries into the library. They removed student identifiers and minimized datasets, which

maximized analyses of demographic and academic trends (e.g., to find out correlations among

undergraduates in humanities departments) while nominally protecting against student privacy

invasions.

The University of Minnesota-Twin Cities (UM-TC) also researched the correlation

between library usage and student outcomes such as retention and grade point average.[86, 87] UM-

TC aggregated usage data from "as many different library services and resources as possible,"

including: circulation loans and renewals; interlibrary loan request; database, e-journal, e-book,

and website usage; instruction activity such as workshop registrations; and online reference

transactions.[88] Whereas HU stripped identifying characteristics from their datasets, UM-TC kept

them intact at the "broad activity" level without tracking granular digital footprints. For example,

UM-TC tracked a student's entry into a database, but not specific queries; they collected

checkout data, but without item titles and metadata.

The library LA literature cites the University of Wollongong (UoW) for pioneering

projects in electronic resource tracking.[89, 90, 91, 92, 93] Rubel and Zhang explain how academic

libraries use authentication technologies, namely Internet protocol (IP) address filtering and

proxy servers, to serve licensed content.[94] Students identify themselves to authentication systems

by logging in, and once logged in they leave traceable digital exhaust that reveals their behavior

to libraries, campus information technology departments, and even publishers. UoW's 'Library

Cube' is "a dataset that joins usage of [UoW library] resources with enterprise systems

containing student demographic data and academic performance using a unique identifier, the

student number."[95] The 'Cube' tracks library-related data also, such as the total number of

student item loans and electronic usage information from proxy server logs, including access

points, timestamps, duration data, and the specific electronic resources with which students

engage. System limitations reduced the authors' ability to glean more information about student

item loans, though they leave unclear what they would have preferred to analyze. In a recent

update, Jantti notes that library data now tells instructors whether students use library resources,

assuming that students are at academic risk when resource usage is low.[96] They report that "[t]he

act of intervention has been positive. When students have been contacted by their lecturer to

query their limited use of Library [*sic*] resources, uptake was immediate."[97]

eBooks also enable data mining of student behavior. Not only do eBook providers

commonly track what individuals read and when, but they also analyze the data to provide

insight into how students read and their comprehension rate.[98, 99] Moreover, eBook add-on

services include user profiles that track reader interests and preferences.[100] Combined with

student demographic data and participatory content from eBook spaces (e.g., collaborative

annotations and resource sharing), eBook activity data may be used in LA research.[101, 102]

Like wider institutional LA projects, academic libraries seek data from their physical

environments via so-called "location intelligence" technologies.[103] The Measure the Future team

is building technical capacity for physical-space surveillance, using computer vision techniques

with open source hardware and software to record and analyze user movements. The project's

leaders argue that sensor data will "allow librarians to make strategic decisions that create more

efficient and effective experiences for their patrons."[104] Academic libraries are also refining gate

count statistics by capturing swipe-card and RFID data from student IDs. For instance, Kent

State University kept detailed demographic and timestamp information obtained from card

swipes, which students were required to provide after the library went to a 24-hour open

schedule.[105] Similarly, Georgia State University captured student information from card swipes,

correlating ingress and egress at specific points in the library with student residential status and

grade point average, among other data points.[106] Other libraries, such as the University of

Oklahoma, have explored using beacon sensors and iOS devices to push customized content and

just-in-time information to users' mobile devices while tracking foot traffic.[107, 108] Walsh argues

that analyzing sensor data about identifiable students moves libraries towards a more informed

understanding of how students interact with and learn in these spaces.[109]

3.2. Ethical problems with LA participation

It is worthwhile for libraries to positively influence student learning outcomes and

develop tighter ties to institutional goals. It is also beneficial for libraries to seek insight into

their value, especially given that library expenditures continue to increase at significant rates

while receiving less and less of their institution's overall budget.[110, 111] Despite its potential

benefits, LA is intertwined with moral problems given the sensitivity of emerging datasets and

the creation of new information flows.[112] These initiatives increasingly develop student

surveillance systems, otherwise known as dataveillance systems.[113] Such systems allow for the

creation of comprehensive digital dossiers that institutional actors can use to make consequential

decisions about students that risk their autonomy.[114, 115, 116] Institutions are purposefully

aggregating massive amounts of student data without limiting "data dredging" for correlations

that could favor values and interests of powerful actors while disenfranchising students.[117, 118]

Also important to note is that the correlation studies on which LA advocates build their argument

do not always account for or prevent against false positives in the statistics; thus, data dredging-

based correlation studies may create misleading and harmful paths of action.

Contemporary scholarship is interrogating the social, technical, and policy-related issues

associated with LA practices.[119, 120, 121, 122] Little has yet been written, however, concerning the

specific challenges facing libraries participating in LA initiatives. A notable exception is in

Showers' *Library Analytics and Metrics* book.[123] Citing Hellman, Showers argues that academic

libraries have been struggling with problems–privacy and otherwise–associated with emerging

data and information flows since social media matured and data analytics became more

accessible.[124] Naturally, libraries want to use these data flows to their benefit and to that of their

users, but at what cost? "Libraries," Showers writes, "may also be undermining some of the

values they have traditionally held so dear" by pursuing analytical insights and creating data-

driven services.[125]

3.3. Ethical codes

In addition to pursuing answers to questions regarding legal compliance, LA advocates

inside libraries and throughout higher education are seeking ethical guidance. Thus far, LA's

problems are so novel and complex that many have more questions than answers. Some useful

ethical guidance has developed out of the two Asilomar conventions on "learning research in

higher education" and "student data and records in the digital era."[126, 127] Similarly, Jisc's "Code

of Practice for Learning Analytics" sets out fundamental principles for institutions to deploy LA

"responsibly, appropriately and effectively."[128]

However, overarching codes such as Jisc's have weaknesses. These codes generally

address LA's potential harms without considering contextual "norms and established values."[129]

These contexts are bound by "canonical activities, roles, relationships, power structures, norms

(or rules), and internal values (goals, ends, purposes)," according to Nissenbaum.[130] So, ethical

codes written to address LA issues at the macro level (e.g., for higher education writ large) fail to

account for the nuances of meso-level contexts (e.g., particular institutions) or even micro-level

contexts (e.g., libraries), much less particular populations those departments serve. For instance,

broad ethics codes are not typically tuned to the needs of vulnerable student populations (e.g.,

first-in-family, poor, of color, with disabilities, etc.). Ethical codes tuned for the needs of more

tightly-bound contexts will often be able to address the conflicts and compatibilities with LA,

whereas general codes may not be able to address specific friction points with existing norms

and values. The American Library Association's (ALA) Code of Ethics is one such fine-tuned

code that can directly address issues with LA.

The Code of Ethics, which has been consistently reviewed and amended since 1939,

guides academic librarians in the United States. In a preface to its eight principles, the code

reads: "Ethical dilemmas occur when values are in conflict. The [ALA] Code of Ethics states the

values to which we are committed, and embodies the ethical responsibilities of the profession in

this changing information environment."[131] The ALA recognizes that the Code is a "framework"

for ethical decision making, not a series of commandments, and that its principles "cannot and do

not dictate conduct to cover particular situations." Research on ethical conflicts in the library and

information science literature have shown that the Code of Ethics only serves as a starting point

for navigating ethical issues.[132, 133] But even though the Code of Ethics does not provide an

action pathway for specific circumstances, it still informs librarians of the profession's values in

ways that more general codes cannot.

We see several conflicts with the Code of Ethics when libraries provide data to, help with

data analysis for, or conduct LA initiatives themselves. LA does not conflict with *all* eight

principles in the Code of Ethics, but the practice clearly implicates the following three principles

(following their numbering in the Code of Ethics):

II. We uphold the principles of intellectual freedom and resist all efforts to censor library

resources.

III. We protect each library user's right to privacy and confidentiality with respect to

information sought or received and resources consulted, borrowed, acquired or

transmitted.

IV. We respect intellectual property rights and advocate balance between the interests of

information users and rights holders.

We take each ethical conflict in turn below in relationship to actual and reasonable hypothetical

practices.

4. Ethical Frictions with Learning Analytics

4.1. Intellectual freedom and censorship

Modern academic librarianship staunchly advocates for intellectual freedom, defined as

"the right of every individual to both seek and receive information from all points of view

without restriction [e.g., censorship]."[134] This focus on receiving information, however, is only

one aspect of intellectual freedom. Dresang adds that intellectual freedom requires particular

conditions that do not restrict thoughts, beliefs, and association with others.[135] And Johnson

contends that intellectual freedom also enables an individual to *create* information, not just

consume it.[136] Summarized, intellectual freedom concerns which information one can access,

how one engages with that information in association with others, and the degree to which one

may create new information.

LA compromises intellectual freedom when institutional actors, system designers, and

algorithms limit opportunities to engage in the creation and consumption of intellectual

materials. So-called "nudging" techniques direct students towards particular learning resources

or to change their behaviors.[137] What connects nudging in learning environments to intellectual

freedom concerns is the ability of an instructor to assess and penalize students for *not* responding

to the nudge. Subsequently, the student may decide always and only to pursue materials

suggested by LA systems, replacing personal intellectual values with those pushed by their

institution.[138]

Consider the following example. Professor Gutierrez uses LA to track his students'

interactions with library resources. He uses the system's features to nudges students away from

and to other resources *he* believes are trustworthy and valuable for student learning. Surely, the

professor has an instructional responsibility to lead students to engage with materials that will

yield positive learning outcomes and experiences. Yet, it is just as plausible that the professor

could "whitelist" some texts and "blacklist" others based on personal preference or political

persuasion–not instructional merit–using LA to nudge students away from these texts. Students

would not be provided the opportunity to engage with these materials, or Professor Gutierrez

could penalize them for doing so once the system alerts him of his students' behaviors. Either

way, tracking and nudging supported by LA limits the degree to which his students can pursue

intellectual materials according to their own interests.

Third-party learning environments that track student behaviors also present intellectual

freedom issues. Educational platforms that provide students access to packaged articles, eBooks,

and other resources via library-vendor relationships may suppress access to specific materials to

promote their contractual goods. In this case, students have less intellectual freedom in that

surveilling actors and systems can carefully craft via rewards, disciplinary processes, and

censorship practices the environment and the materials students encounter; in so doing, they limit

a student's opportunity to "seek and receive" information. When students depart their institutions

and lose access to vendor-controlled walled gardens, they are liable not to know how to seek

appropriate information elsewhere.

Ethical concerns also arise around tracking student social networks within and outside

LMSs. Desire2Learn, a commonly used LMS, can map social networks as they develop in course

sites to provide instructors insights into who is communicating with whom, when, and how

often. Instructors and advisors could use such maps to route students to communicate with

particular peers. While it may be beneficial to redirect student communications to include

students on the fringes of the network or even match students who have not connected,

individuals may just as easily manipulate the network and do harm. For instance, instructors may

direct students away from peers that present opinions in opposition to their own, or individuals

they deem trouble students. Research has uncovered how institutions are already correlating

student presence in campus physical spaces such as libraries via WiFi access logs.[139] Using such

analytics to try to direct student relationships (e.g., to nudge students to interact with higher-

achieving peers) would be egregious, but institutions might believe this surveillance-based

practice may bolster student achievement. Associated intellectual freedom issues are less about

the liberty to interact with and consume materials, and more about the *social conditions*

necessary to exchange ideas freely among peers. When institutions use social network data to

manipulate interactions in academic spaces, they damage the free and organic exchange of ideas.

4.2. Privacy and confidentiality

LA naturally invokes privacy issues and concerns about confidentiality of personal

information. Student use of materials (e.g., books, articles, etc.) may be recorded, analyzed,

shared with a variety of actors, and used to intervene in student learning and life choices. These

practices in turn damage intellectual freedom. While not explicitly developed in the Code of

Ethics, the concern over intellectual freedom and user privacy and confidentiality refers to

theories of "intellectual privacy" developed by Richards.[140, 141] Intellectual privacy is the

protected sphere in which we can cognitively function and safely develop speech without

intrusion.

Librarians commonly help instructors develop LMS-hosted courses by embedding

resources–articles, links, etc.–for students to access. This service was benign and welcome in the

past. Today, however, LA technology tracks when students click on resources linked from or

embedded within course sites, as well as how long students read (i.e., view) the resource, which

enables actors with the right privileges to keep a detailed audit of these activities and,

consequently, judge students' behaviors.

LA data is often inaccurate because it cannot tell when students are actively reading and

interacting with a resource based on clickstream data alone. It may be that students open a PDF

in the LMS only to walk away to socialize with peers in the hall of their dormitory or purchase a

cup of coffee; alternately, students could simply print off the PDF. Furthermore, it could also be

that students track down the reading using a citation instead of clicking through to the reading in

the LMS. Any of these three situations would incorrectly calculate student engagement scores.

As LA matures and the technology moves away from clickstream data, it could get more

accurate engagement data by capturing mouse movements or eye movements via computer

cameras.

We have seen in our own experience how instructors are increasingly relying on this

inadequate data as a proxy for attendance and to assess student engagement, which aligns with

insights from Kruse and Pongsajapan.[142] Besides being unfairly graded, the harm for students is

that they may shift the intellectual resources they pursue toward those included in the

surveillance net and used to grade their progress, eliminating other options. Moreover, they may

look upon their instructors, librarians, and others with access to their data with "coded

suspicion,"[143] which can lead to distrustful relationships and negatively impact "intellectual risk-

taking."[144]

UoW's 'Library Cube' analytics project tracked student use of library resources, noting

how usage of library sources immediately increased when instructors informed students that their

usage was low. Uptake responding to an intervention may seem to be a benefit of library LA

projects, but this finding does not consider potential *adverse* psychosocial effects. Without

empirical data to say otherwise, it is just as plausible that students responded with fear that what

they thought to be personal, private information (i.e., which resources they accessed) would be

used to their disadvantage. In response, they increased their library usage to regain favor with

their instructor, but not because they believed it would intellectually benefit them. It is equally

disconcerting that some students may come to believe there is some "correct" threshold of library

usage or "right" materials they should access. We expect these initiatives to increase library

anxiety and decrease trust toward librarians among students, especially urban students of color

whose have historically been the target of school surveillance.[145]

Students may chill their intellectual behaviors due to privacy invasion from librarians

participating in LA. We should be concerned not only about how this negatively impacts

individual student lives, but also how chilling can impact campus and classroom communities.

Chilling brought about by LA can harm the sharing of viewpoints and decrease pushing

intellectual boundaries, both of which often require learner communities to engage in free,

unrestricted speech and inquiry.[146]

4.3. Intellectual property rights

The nascent value LA attaches to student data could significantly affect intellectual property (IP) negotiations between digital content vendors and HEIs. These IP concerns interact with digital rights management (DRM) requirements (e.g., to protect copyrights) attached to library-vendor contracts, and surface how informational and algorithmic products derived from student data could become trade secrets or marketable products. Since access to data is enticing for vendors and institutions alike, librarians will have to navigate ethical quandaries around capturing and providing interaction data about student access to library resources with vendors. Content vendors track student usage of their digital materials, nominally to protect against illegal access and sharing. In response, the ALA recently proposed guidelines addressing increased tracking:

> [M]ost e-book and digital content vendors collect and use library patron data for a variety of reasons, including digital rights management, consumer analytics, and user personalization. Libraries and vendors must work together to ensure that the contracts and licenses governing the provision and use of digital information reflect library ethics, policies, and legal obligations concerning user privacy and confidentiality.[147]

The statement highlights a growing tension between digital content providers wishing to track access and librarians who advocate for user protections against tracking. As Rubel notes, however, resolving the "trade-offs between patron privacy and access" to digital resources has proved challenging.[148]

The *Harvard Business Review* (HBR) controversially limited use of their articles in digital course packs and electronic reserves by inserting licensing language into an EBSCO

package contract that included HBR.[149, 150] HBR held that its license–as enacted through

EBSCO–trumped any fair-use claims to link to or copy articles for student access outside of

EBSCO's system. Such licensing language and restricted user access funnels users to vendor-

managed systems that track users. Lambert, Parker, & Bashir's research into popular digital

content vendors found that vendors often collect, analyze, and share personally identifiable

information with third parties, even though public policies stated otherwise.[151] And Rubel and

Zhang's investigation into 42 unique licensing agreements uncovered the wide spectrum of data

collection and sharing protections in existence (or in some cases lacking altogether).[152] This

suggests that libraries are participating in a "Faustian bargain" whereby vendors and vendor

systems provide access to valuable resources at the cost of degrading student privacy and

weakening librarians' professional ethics commitments.[153]

Vendors or other actors seeking access to student data creates another IP concern: trade

secrets. Institutional advantages gained through LA are believed to enable HEIs to position

themselves strategically in a "competitive and dynamic" marketplace.[154] To give student data or

derived findings away could diminish the value gained. Therefore it is plausible that HEIs are

likely to protect their data assets as trade secrets, gaining revenue therefrom through the sale or

license of specially curated databases and informational reports, analytic workflows, or custom-

made algorithms.

Efforts by HEIs to maximize trade-secret revenue may force librarians into data mining

they find unsavory. Early library LA research suggests important correlations between library

usage data and student learning outcomes, which HEIs may seek to understand at more granular

levels. Doing so, however, will require librarians to monitor student behaviors in physical and

digital spaces to determine which behaviors correlate with higher academic achievement or

social integration into campus life. HEIs may also pressure libraries to negotiate for licensing

contracts that require vendors to contribute student behavior data from their systems to

institutional LA data warehouses.

5. Recommendations

5.1. Embedded values

ALA's Codes of Ethics and the values that inform it give professionals strength and

direction during times of socio-technical change. Although the technological momentum behind

Big Data seems to legitimize similar practices in many corners of society, LA is still an open

system that many actors–including librarians–can still influence. The question, then, is how

librarians should react to the development of LA initiatives.

We believe librarians should proactively embed their professional values in LA practices

and technologies through advocacy. Emerging socio-technical systems often demand political

resistance, especially when powerful parties are positioned to be the primary benificiaries.[155, 156]

As LA matures, the values that librarianship supports risk damage from institutional actors who

do not share the same ethical perspective and values. Though library values cannot overrule

other departments and offices supported by other professional ethics codes, librarian inactivity

will cause professional values to be ignored or suppressed.

It is not our aim herein to suggest principles or strict policy recommendations around LA,

though work in this area is ongoing. The National Information Standards Organization's work on

user privacy and library, publisher, and vendor systems provides useful policy recommendations,

as does Asher and Hinchcliffe's work specifically related to LA and libraries.[157, 158] Instead, we

advance recommendations for librarian participation in the evolution of LA initiatives on their

respective campuses. None of the following recommendations preclude librarians from pursuing

assessment studies, but they do require a higher level of ethical practice should they seek to

study student behaviors as evinced in data-based systems.

We recommend first that librarians explain and advance the profession's ethics while

participating in dialogue around LA initiatives with their institutional and professional peers.

Second, librarians can help build campus-wide data governance mechanisms to oversee

potentially harmful information flows. Finally, librarians should develop library-specific

information policies as well as participating in building institution-wide information policy to

govern the ethical use of LA technology. We take each of these recommendations in turn in the

following sections.

5.2. Advocacy and constructive dialogue

It is the responsibility of librarians to advocate for library values and ethical positions by

participating in conversations about and design of LA systems at their institutions and within the

profession. Wearing librarianship's "ethical standards as badges of honour [*sic*]" without acting

on them risks eroding those standards.[159] Librarians must communicate why their values are

important, how their ethical perspective conflicts with LA practices, and the ways in which LA

initiatives harm students, especially with respect to intellectual freedom and privacy.

Librarians can also serve as ethical exemplars for other HEI actors. Taking the ethical

high ground puts pressure on institutional peers to make explicit commitments about data

security, governance, and appropriate use and justify data ethics. For instance, several libraries

have consciously employed consent-based research using ethnographic methods to demonstrate

library value and develop an improved understanding of how library services and collections

interact with learning outcomes.[160] To leverage their principled actions, librarians need to get a

prominent seat at the tables where LA conversations occur. Librarians should talk about their

past successes and discuss how they can gain actionable insights without imperiling student

intellectual freedom and privacy by trawling through student data.

It is also important for librarians to extend these conversations outside their institutions

into their professional circles. Library professionals need to share their success and failures with

LA, as well as how they navigated hard conversations concerning ethics. Librarians should be

ethically introspective and openly reflect about the justifications they use to push forward or pull

back from LA. Librarians have a duty to, among other things, participate in ALA committees;

present at local, state, and international conferences; and publish in professional and scholarly

outlets to share their experiences. It is only through these conversations that the profession will

find its ethical bearing with respect to LA.

5.3. Data governance

Developing data warehouses to account for emerging information flows and determining

the conditions under which actors should have access to data and information involves

significant governance challenges.[161] Institutional data governance needs naturally overlap with

data management services that librarians have been building capacity for over the last few

years.[162, 163] HEIs would benefit from including librarians in data governance talks because of

librarians' technical and conceptual expertise. More importantly, however, adding librarians to

data governance teams provides another opportunity for library professionals to challenge

ethically suspect data flows and analytics, while shaping governance practices to protect

intellectual freedom and privacy.

5.4. Information policy

Librarianship's values would ideally be embedded in library and institutional policies as "normative propositions" that drive data and LA practices, in so doing protecting the interests of students and libraries.[164, 165] To accomplish this, librarians need to advocate for the profession's values with institutional policy-makers when they design internal policy documents, memoranda of understandings with partner institutions, and legally-binding contracts with third-party service providers. Moreover, such policies may influence the design of LA systems, as those systems would need to respect policy regulations before institutions enter into contracts with vendors.

This might improve librarians' position in licensing discussions with content vendors as well. If librarians are proactive participants in policy construction they will have the powerful backing of their institutions during these sometime contentious negotiations. They could, for instance, require vendors to disclose behavioral data they gather, how long they keep it, and what they do with it. Moreover, they could negotiate licenses that minimize the data gathered as well as its retention period, and enable HEI oversight of vendor data practices via license agreements.

6. Conclusion

Though pursuing LA may lead to good outcomes for students and their institutions, higher education and the library profession still face an ethical crossroads. LA practices present significant conflicts with the ALA's Code of Ethics with respect to intellectual privacy, intellectual freedom, and intellectual property rights. We recommend that librarians respond by strategically embedding their values in LA through actively participating in the conversations, governance structures, and policies that ultimately shape the use of the technology on their respective campuses. Information ethicists, empirical researchers, and practitioners alike must

deeply consider the ways in which these data-driven practices may pervade and erode

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Abbreviations

ALA = American Library Association

DRM = Digital Rights Management

HBR = *Harvard Business Review*

HEI = Higher education institution

HU = Huddersfield University

ILS = Integrated library system

IP = Intellectual property

LA = Learning analytics

LMS = Learning management system

UM-TC = University of Minnesota-Twin Cities

UoW = University of Wollongong