Conflicting Values: An Exploration of the Tensions between Learning Analytics and Academic Librarianship

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Abstract

The prevailing rhetoric concerning learning analytics is that its use will support the educational endeavor and make significant improvements to teaching and learning. For academic libraries, learning analytics presents the possibility of using library data to coordinate, integrate, and align with the goals of the institutions in which they are embedded. While libraries have a long history of collecting data to support various service and learning objectives, those data have typically been siloed, de-identified, private, and confidential. Although there are positive contributions that learning analytics can make to the learning process, there are concerns associated with its use, particularly the tensions between the objectives of learning analytics contrasted with different conceptualizations of learners and the values of education and librarianship. Institutions of higher education use learning analytics to achieve institutionally defined goals and outcomes for students, which creates tensions with the enshrined values of the American Library Association's *Code of Ethics*, *Library Bill of Rights*, and *Core Competencies of Librarianship*. The transcendent benefits to society that are inherent in education and academic librarianship, such as the rights and responsibilities of citizenship, are not measurable through learning analytics.

Introduction

Across postsecondary institutions, there is an increasing call to harness the power of learning analytics (LA) to better understand student behavior, demonstrate efficiencies in human and resource management, improve learning outcomes, and to decrease student and institutional costs (Jones

and Salo 2018). Learning analytics involves using learner-generated data to optimize the immediate learning environment. As noted by Jones and LeClere (2018), the use of learning analytics in academic libraries is a trend that raises critical questions concerning the collection, identification, aggregation, and management of a wide variety and volume of data about students, the role of educational technology, and the role of librarians. Conversely, in a seminal OCLC report, Connoway et al. posit that learning analytics are central for academic librarians to "(1) communicate the library's contributions; (2) match library assessment to the institution's mission; (3) include library data in institutional data collection; (4) quantify the library's impact on student success; (5) enhance teaching and learning; and (6) collaborate with educational stakeholders" (ACRL 2017, 1).

The objectives mentioned in the above OCLC report are laudatory; however, enacting or achieving these goals, along with the increasing use of learning analytics in the educational sector more broadly, reveals the tensions between the objectives and desired outcomes of learning analytics and the values and core competencies underpinning education and librarianship. Learning analytics raises deep philosophical questions about the nature, role, and purpose of education and the university as a social institution, and the role of academic libraries in supporting teaching, learning, and research. Learning analytics might connect and support learners and assist institutions in meeting student learning outcomes, but might just as easily disconnect and alienate learners and undermine the educational endeavor. This is an important consideration, particularly as learning analytics privileges individual development over the social and cultural aspects of education, such as the rights and responsibilities of citizenship. Learning analytics challenges us to reconsider the broader purposes of education in democratic societies and to question the potential and limitations of big data, including learning analytics, in supporting education and providing insight into the learning process. Furthermore, assumptions about the value of data and what they do or do not indicate or infer, and the processes, procedures, and methods involved in deriving insight from learning analytics, may lead to partial or even erroneous conclusions and findings about a complicated endeavor: human learning.

While learning analytics is a recent development, academic librarians have a long history of collecting and using library data to assist in internal decision-making, to justify library budgets and activities, to improve services, and to identify broader trends in the use and value of information and libraries (Hiller and Self 2004). Typically, these data are de-identified and used within the library for assessment, evaluation, and quality-assurance activities. Library data have not historically been collected in order to be aggregated or collated with other institutional datasets, identified, and

used to support institutional goals (Hoel, Chen, and Gregersen 2018). Using datasets collected from people's interactions with the academic library can create a quandary for academic librarians because this action can be interpreted as conflicting with professional values (Prindle and Loos 2017). Significantly, learning analytics in academic libraries may conflict with Article VII of the American Library Association's (ALA) *Library Bill of Rights,* which was revised on January 29, 2019. Article VII reads:

> All people, regardless of origin, age, background, or views, possess a right to privacy and confidentiality in their library use. Libraries should advocate for, educate about, and protect people's privacy, safeguarding all library use data, including personally identifiable information. (ALA 2019b)

The revised *Library Bill of Rights* specifically points to protecting "people's privacy, safeguarding all library use data, including personally identifiable information." For some, the interpretation of Article VII may not conflict with using learning analytics in the library, whereas others may interpret it as a direct conflict with professional values.

Furthermore, while an emerging body of literature discusses the ethical dimensions of learning analytics as it relates to privacy and confidentiality (Ekowo and Palmer 2016; Prinsloo and Slade 2016; Siemens 2013), learning analytics and big data approaches may not be governed by the rigorous standards set by research ethics boards and protocols. Consequently, questions arise about issues such as research ethics (e.g., data withdrawal, informed consent, and determining who controls the data and who is accountable for data breaches); research purpose (e.g., what questions can be explored using learning analytics and who benefits); research design (e.g., emphasis on quantitative approaches over qualitative, assumptions about the explanatory power of data); data collection (e.g., prioritizing technology for data collection); and data analysis (e.g., correlation versus causation, and limitations). The introduction and use of learning analytics in higher education have implications for academic librarians and library and information studies (LIS) education, particularly as they relate to *ALA's Core Competencies of Librarianship* section 6 on research (ALA 2009). The use of learning analytics in academic libraries should motivate LIS professionals and educators to reflect on library values and ethics (holistically, and across all fields of professional practice, but particularly in terms of research); core competencies in librarianship, including research; and the differences between technical training versus education. In addition, while learning analytics might align with some of the priorities of higher education, are learning analytics technologies in academic libraries fundamentally incompatible with the higher-level values of education and libraries, such as promoting an engaged citizenry, supporting democracy, and fostering lifelong learning?

LEARNING ANALYTICS

The fuel of learning analytics is data. The advent of the personal computer, content-management systems, and other educational information and communication technologies (ICTs) have facilitated the generation and collection of "digital traces" or "digital trails" that are often generated by people unknowingly. Borgman (2018) suggests that there are two divergent trends regarding data collection in universities: providing access to research data in order to meet open access commitments; and the collection and aggregation of what she dubs "grey data." Gray data are the data generated from all university stakeholders, including students, staff, faculty, and administrators engaged in a myriad of administrative, research, teaching and learning, and service activities. Data-rich universities and other postsecondary institutions are increasingly seeking to capitalize on gray data to improve student learning outcomes via learning analytics. Significantly, the assumption among learning analytics enthusiasts is that these digital data are valuable because they imply something important about how students learn and how interventions might help them learn "better" (Clayton and Halliday 2017). Learning analytics, then, offers a way for gray data to be collected and analyzed for patterns, insights, and correlations in order to provide students with personalized and adaptive materials. According to Conole et al.,

> Learning analytics 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. (2011, i)

This definition places students at the center of the analytics enterprise and emphasizes the core purpose of learning analytics as improving student learning and outcomes by understanding, enhancing, and providing insight into the teaching and learning process and student behavior. This work aims to understand the cognitive and behavioral factors that influence learning, such as the "capacity of learners, learning behavior, predictability of learning concerns, and nurturing of cognitive aspects of learners" (Pinnell et al. 2017, 125).

Learning analytics as a field of research has existed since at least 1995, and two comprehensive bibliometric analysis studies indicate that there has been an exponential increase in learning analytics research beginning in 2011 (Waheed et al. 2018; Zhang et al. 2018). Learning analytics has been described as a research discipline that encompasses technical, social, and pedagogical domains, and a transdisciplinary paradigm (Gašević, Kovanović, and Joksimovića 2017; Peña-Ayala 2018) that examines educational labor from the perspectives of various actors such as students, instructors, and administrators, and where data are collected and queried using a wide array of tools and techniques. To analyze data, learning analytics employs "techniques such as predictive modeling, building learner

profiles, personalized and adaptive learning, optimizing learner success, early interventions, social network analysis, concept analysis, and sentiment analysis" (Siemens 2012, 5), to name but a few approaches. Clow (2013) notes that learning analytics takes an "eclectic approach" and that the field lacks a coherent epistemological basis. In addition, writing in a special issue on methodology and learning analytics, Bergner, Gray, and Lang (2018) recognize that while learning analytics draws on a wide variety of expertise, methods, and different disciplines, methodological clarity is necessary for the field to mature, define boundaries, and make and support claims. The use of learning analytics in higher education and particularly academic libraries provides the opportunity for critical reflection on the ways in which learning analytics conflicts with professional library values; core competencies, particularly research competency; ethics; and the broader purpose of education.

Learning Analytics in Higher Education

Potential Benefits of, and Concerns with, Learning Analytics in Education
Much of the rhetoric about learning analytics positions it as a means of improving educational practices and student learning outcomes and as beneficial to all university stakeholders, including students, faculty, and staff. For example, the 2016 *NMC Horizon Report* predicted that learning analytics would be one of the largest emerging fields in education and reported that "through data-informed solutions that reduce the time to degree completion, improve student outcomes, and target students for recruitment, learning analytics are benefiting a range of stakeholders beyond learners and instructors, to bodies of governance, researchers, and institutions" (Johnson et al. 2016, 38). This sentiment was repeated in the 2018 *NMC Horizon Report*: "Analytics can benefit areas including students' time to degree, learning outcomes, recruitment, alumni relationship management, and research productivity" (Becker at al. 2018, 38). Similarly, the UK Higher Education Commission concluded that learning analytics had "enormous potential to improve the student experience at university" (2016, 4), and the US Department of Education described learning analytics as "meaningful and relevant to learners, driven by their interests, and often self-initiated" (2017, 9). The potential of learning analytics has created a sense of excitement among institutions of higher learning that genuinely align with the progressive ideals of learning analytics to benefit students and positively shape the student experience of postsecondary education.

In contrast, in their analysis of 252 research papers on learning analytics, Viberg et al. (2018) found that just 9 percent of studies offered evidence to indicate that learning analytics improved student outcomes and that only 18 percent of studies mentioned ethics or privacy. Learn-

ing analytics raises the issues of data stewardship and ownership, privacy, protection, academic freedom, accountability, informed consent, and transparency, among others (Borgman 2018). As Carmel (2016) notes, in the European K-12 sector, schools collect student-generated data in order to inform decision-making, but they increasingly rely on vendors to collect, aggregate, process, and analyze data generated by, and about, students. Smaller postsecondary institutions that do not have in-house capacity for data gathering, storage, and analysis may need to rely on private companies and vendors to provide these services on their behalf, thereby transferring power from the public sector (e.g., public universities) to the private sector. Furthermore, reliance on vendors and private companies to provide these services has consequences for data analysis because companies are constrained by the data-analysis tools at their disposal, and thus they can only analyze data in ways that their tools permit. In learning analytics, tools drive discovery, and these tools are firmly in private company control (Ekowo and Palmer 2016).

The datasets, tools, and processes related to learning analytics are situated within parent institutions that are themselves beholden to broader social forces that demand universities demonstrate their value, often using models from the private sector, and that they are accountable for student learning experiences and outcomes. Oakleaf suggests that learning analytics is a positive development in this regard:

> Learning analytics initiatives seek to increase student success and improve institutional business models. . . . They are aware that their institutions are increasingly asked to demonstrate that they are delivering valuable learning experiences for students, assessing those learning experiences effectively, and intervening to assist struggling students when necessary. (2016, 473)

Undoubtedly, postsecondary institutions, and universities in particular, are increasingly corporatized, and the demands on institutions to demonstrate value are real. Nonetheless, it is important to recognize that universities, as a part of their core missions, have been delivering valuable learning experiences; providing helpful assessment, evaluation, and feedback; and intervening to assist struggling students for centuries. Furthermore, in a potentially negative feedback loop, increased pressure to demonstrate value, meet student learning outcomes, and pressure from the private sector on institutions to purchase tools and services and provide access to student data, can result in privileging data that provides evidence that these very standards are being met (Clayton and Halliday 2017). And, as Rubel and Jones write, "institutional goals and student benefits are not identical, and conflating them risks subordinating student benefits to institutional goals" (2016, 153), thereby undermining one of the main justifications of using learning analytics in postsecondary education.

Big Data in Education

While there is no rigorous definition of big data (Mayer-Schönberger and Cukier 2014), they are generally defined by their characteristics in that they meet the five *Vs*: volume, velocity, variety, veracity, and value (Ben-Porath and Harel Ben Shahar 2017). In an educational context, big data that might be collected and measured about students includes absences, lateness, tracking time on the e-learning system, reading behaviors, grade point average (GPA), discussion posts, progress on assignments, etc. Another feature of big data in an educational context is that they are structured and unstructured and so large that human beings are unable to process or interpret them without the use of tools, techniques, and technology such as those used in learning analytics. Some of the potentially beneficial uses of big data in education include "unprecedented capacity to collect large and diverse data sets in naturalistic learning environments" (Dishon 2017, 282), and the ability for researchers to select methods beyond merely choosing between "rich qualitative descriptions or isolated quantitative results" (Dishon 2017, 282). This suggests a major advantage of using big data in education is that it enables the correlation and analysis of multiple factors over time, resulting in dynamic and formative findings rather than summative and linear ones (Dishon 2017). As well, big data analytics can potentially offer insight into complex learning processes that historically have been difficult to operationalize and measure because many variables can be analyzed at the same time. Adejo and Connolly (2017) similarly note that the potential of learning analytics to broaden the focus from bivariate analysis to multivariate analysis can yield deeper insights.

However, the promise of learning analytics is predicated upon assumptions about big data and objectivity. Dishon notes that "the perception of big data's objectivity is reflected in the term 'data-mining,' which implies that data are a natural resource waiting to be mined" (2017, 278). The assumption here is one that is true of both big and small datasets—only variables that are measurable are included in the analysis. Further, data are partial representations of some phenomenon and are unable to fully model or describe reality. Therefore, "data are never 'raw' nor objective," although they are often treated as such (Oliphant 2017, 13). Jones and Salo suggest "that the correlation studies on which learning analytics 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" (2018, 310). Learning analytics can track some data but not others, and the decisions about what to include and exclude can come at a cost with respect to other goals of education and the complex process of learning. Further, Dishon draws on the work of Perrotta and Williamson (2018) to argue that "the tendency to equate increased quantification with increased objectivity still plays a crucial role at the levels of policy and practice" (2017, 278). And,

more importantly, Noble's (2018) work on algorithms—step-by-step procedures for solving a computing problem—demonstrates how data-driven algorithmic analysis can be used to discriminate. Decisions about what data to collect and how to analyze them are not value neutral.

In addition, big data and learning analytics assumes a statistically determined "normal learner." Clayton and Halliday (2017) suggest that if these presuppositions about students themselves and the learning process are flawed, then consequently, so too are the insights gleaned from the data. The authors provide a concrete example of how this might unfold by invoking a number of different interpretations of data that indicate one student is taking longer to read an assigned text compared to others. A possible interpretation of the data is that the student may be a slow reader, who may or may not be struggling. Other interpretations are that they may be more engaged with the material, they may need more time for deeper comprehension, or they may be attending to another matter while they are simultaneously logged in to their online learning content-management system. The problem is that variables such as "time on task" are easy to quantify and measure, and therefore easier to replicate and scale up, which provides insights into very specific activities. The example of reading is an important one because not only is reading foundational to acquiring an education, it is a tremendously complex activity that is not easily scalable or measurable. Examples include an extensive and established body of LIS research on reading practices, highlighting the ways that people engage in different reading behaviors at different times for different purposes (see Rosenblatt 1978); the importance of multiple texts in literacy development (Mackey 2016); and the effects of reading for pleasure on academic performance, social engagement, and personal development (Howard 2011). None of these reading activities are measurable via learning analytics.

Furthermore, Clayton and Halliday (2017) suggest that the very idea of academic merit or defining the criteria of what makes a "good" student might be shaped by data and patterns that presume a homogenous student body rather than a diverse and distinct set of individuals who may have little in common. Similarly, in their papers on big data and education, Ben-Porath and Harel Ben Shahar (2017) and Scholes (2016) argue that the collection and aggregation of large quantities of minute student behavioral and cognitive data might "flatten" the phenomenon that the data represent and render individual students invisible. For example, in a study on the use of learning analytics and student advising, advisors emphasized "that knowing their advisee, the 'whole student,' was necessary in order to determine best to tailor interventions and provide advisees support. This was not a simple process, and it often took significant effort to develop a trusting relationship between the advisor and advisee" (Jones 2019, 445). While it is beyond the scope of this paper to discuss the power of education in social integration, it is important to be mindful that the

data used by learning analytics is generated by individuals with a diverse range of backgrounds, abilities, life experiences, achievements, and hopes and dreams, and that no amount of data will be able to fully represent them (Jones and McCoy 2019). This is an important issue for academic librarians in their roles to support teaching, learning, and research, and is a helpful reminder of the individuality embodied in the people academic libraries serve.

At the same time, the appropriateness of using big data techniques and learning analytics in the educational sector raises questions about the purpose and nature of education and who profits (Lynch 2017). Clayton and Halliday (2017) argue that education is a good distinguishable from other goods because people do not consume it at their discretion, particularly in K-12, and it is delivered coercively in that learners do not have choices in the content of the material that they learn. Conversely, education is personalized to the individual because each learner brings their personal histories, experiences, preferences, and abilities to the material (Boyte 2017). A critique of personalized learning is that it promotes a conception of education as a set of discrete skills and behavior modifications, which ignores the social embeddedness of learners and culturally relevant knowledge (Roberts-Mahoney, Means, and Garrison 2016). Similarly, Dishon argues that for John Dewey, the most important aspect of education was the social—including development of social and civic skills, such as argumentation and collaboration, interactions with peers, and the "importance of participating in activities one has not chosen for herself" (2017, 282), over individuals making personal choices about their learning.

Learning analytics promotes personalized learning, personalization of materials, and personal profiling, and it caters to individuals rather than attending to the social and relational aspects of learning (Harel Ben Shahar 2017). What the above authors point to is the ways in which big data and learning analytics privilege individual and personalized learning over social learning, and more importantly, how this may obfuscate one of the purposes of education and a core mission of universities: to educate and train for citizenship. These issues are pertinent to the professional practice of librarianship and LIS education in terms of values, core competencies, and transcendent benefits that emphasize the social.

Learning Analytics and Academic Librarianship

Libraries and librarians are increasingly viewed as having an active role in learning analytics, with proponents arguing that learning analytics provides a means for libraries to demonstrate their value to, and align with, their institution's goals. Libraries have historically been keen data collectors, including counting virtual library visits, gate counts, and reference questions, to name but a few examples. Historically, there have been two important conditions of library data collection: these data were both de-

identified, as well as siloed, which rendered them less useful in aligning with institutional goals or the ability to correlate library use with student learning outcomes (Jones and LeClere 2018). It is through the processes of data sharing, integrating institutional datasets, and creating identifiable data that possible correlations between student library use and GPA, for example, can be made. Siemens (2012) and Oakleaf (2018) point out areas where librarians can be involved in connecting data and people from across a wide array of research domains through data sharing. In this way, librarians can play an active role in the learning analytics enterprise.

Jones and Salo (2018) list a number of ways in which learning analytics has been taken up by academic librarians in recent years. Through the collection of gray data that reveals individual behavior, these learning analytics projects track database, e-journal, e-book, and website usage; online reference transactions; the use of authentication technologies such as Internet protocol (IP) address filtering and proxy servers; individual e-book reading behaviors, including what individuals read and when, comprehension rate, as well as reading interests; and traceable student logins. Other learning analytics projects include using tracking technology in the library to better understand how people use library space. The collection of these data raise a number of critical questions from a values and core competencies perspective: Does collecting these data conflict with the core values of librarianship such as protecting people's privacy and confidentiality? Does tracking reading behavior, comprehension, and interest violate intellectual freedom principles? Can students opt out from library data collection? Other questions raised in terms of LIS core competencies, and particularly competency "6. Research" (ALA 2009), include the following: Who owns these data and who can use it? How do librarians handle informed consent? Who is responsible for data breaches? These are particularly important questions as libraries move to provide research data-management services. While learning analytics supports some of the goals of higher education, in what ways does learning analytics conflict with ALA professional values and transcendent values?

Learning Analytics, Librarianship, and Values
Oakleaf argues that there are several points of intersection among learning analytics, learning assessment, and the practice of librarianship, in terms of shared values.

> Learning assessment and learning analytics share a number of common values that librarians espouse. Both approaches demonstrate the importance librarians place on students' opinions, positive affect, confidence, self-efficacy, attainment of learning outcomes, commitment to growth and improvements, and ultimate success—whether that success is represented by retention in a program, minimized time to degree, GPA or similar achievement measures, speedy and appropriate employment, lifelong learning, or some other long-range goal. (2016, 472)

While one of the above goals is supported by the American Library Association's *Core Values of Librarianship*—the value of lifelong learning (ALA 2019a)—"minimized time to degree" and "speedy and appropriate employment" are not. Furthermore, Oakleaf's labelling of both learning analytics and librarianship as "approaches" undermines the value of professional practice and the value of the education a degreed professional receives by implying a false equivalency between learning analytics and an ALA-accredited master's degree program.

In addition, the 2016 *NMC Horizon Report* defines learning analytics as "an educational application of web analytics aimed at learner profiling, a process of gathering and analyzing details of individual student interactions in online learning activities" (Johnson et al. 2016, 38), where the key word, *profiling*, indicates the mechanism by which learning analytics can be applied and tailored to individual students. Profiling requires the collection of identifiable patron information that may compromise patron privacy and confidentiality. The ALA document *Privacy: An Interpretation of the Library Bill of Rights* states:

> In a library (physical or virtual), the right to privacy is the right to open inquiry without having the subject of one's interest examined or scrutinized by others. Confidentiality exists when a library is in possession of personally identifiable information about users and keeps that information private on their behalf. Confidentiality extends to "information sought or received and resources consulted, borrowed, acquired or transmitted" (*ALA Code of Ethics*), including, but not limited to: database search records, reference questions and interviews, circulation records, interlibrary loan records, information about materials downloaded or placed on "hold" or "reserve," and other personally identifiable information about uses of library materials, programs, facilities, or services. (ALA 2014, para. 2)

Not only does learning analytics potentially compromise privacy and confidentiality, Landgraf (2018) suggests that if one is aware they are being tracked, they might change their behavior or self-censor. One may be less likely to engage with controversial materials or materials that reveal something about oneself that one wishes to remain private. These concerns impinge on freedom of expression. Similarly, Jones and LeClere argue that privacy invasions can impede the free flow of information and ideas, which can then lead to "informational harms," which are the ways in which information "can coerce, to nudge, and to limit individual actions in ways that run counter to their personal interests or limit their autonomy" (2018, 363). As Bejtlich admonishes: "If you can't protect it, don't collect it" (2015, para. 1). Consequently, learning analytics approaches may be interpreted by academic librarians as contravening ALA ethics and values, with Jones and LeClere stressing that "institutions cannot assume that all librarians are willing to participate in LA practices" (2018, 358).

The ALA's *Core Values of Librarianship* outlines a number of values such

as "the public good, democracy, education and lifelong learning, and social responsibility." These values are, according to Town (2011), the "higher order benefits" that libraries provide that are difficult to measure. Town, writing about academic libraries specifically, argues that

> the aims of the academy and scholarship are transcendent, relying on a shared belief that there is an impact through higher education on individuals and society, and beyond that there is a value arising from being educated, which relates in a fundamental way to human flourishing. This has always been difficult to quantify and measure. (2011, 112)

While not ignoring the importance of demonstrating library value in terms of metrics such as return on investment, for example, Town develops a "values-scorecard" for the academic library. The scorecard outlines some of the transcendent values of libraries such as "cocreation and custodians of knowledge, assisting students to achieve their full potential" (2011, 123), and relationship building. These values and benefits are difficult to measure using only learning analytics and point to the necessity of emphasizing values and the broader social benefits of libraries in articulating library value.

Learning Analytics, Librarianship and Core Competencies
Learning analytics raises questions about professional knowledge, core competencies, and LIS education. According to the *ALA's Core Competencies in Librarianship,* all students in an ALA-accredited master of library and information studies (MLIS) program or equivalent should acquire the core competencies enumerated under "6. Research" during their degree program. These competencies are the following:

> 6A. The fundamentals of quantitative and qualitative research methods.
> 6B. The central research findings and research literature of the field.
> 6C. The principles and methods used to assess the actual and potential
>   value of new research.
> (ALA 2009, 4)

The *ALA's Core Competencies in Librarianship* research competencies stress the importance of "traditional" research methodologies, methods, and knowledge production in the discipline of LIS and in professional practice. Academic librarians have undertaken rigorous quality-assurance activities and qualitative and quantitative studies to evaluate services, collections, and library use, for decades. In the research process, research questions drive data collection, data analysis, and methodological concerns. Conversely, research questions do not necessarily drive the processes, procedures, and approaches used in learning analytics. As such, the use of learning analytics in libraries may divert attention from the myriad research activities that librarians engage in, such as deriving evidence from consulting the research literature, undertaking rigorous and

systematic studies, assessment and evaluation, evidence-based practice, and sustained engagement with users. Furthermore, as Berry states, big data "provide destabilizing amounts of knowledge and information that lack the regulating force of philosophy" (Berry 2011, 8). Within the field of LIS, there is a formalized approach to research that is informed by theory and that acknowledges the limitations of methods, data analysis, and knowledge claims.

Learning analytics is a combination of method and technique (Papamitsiou and Economides 2014). Pinnell et al. (2017) discuss the differences between learning *analytics* and *analysis* and explain the ways in which data analysis is linked to a specific process of posing research questions, gathering data, running a statistical test, and providing evidence to support claims. The authors write that "analytics exists overtop of this view of analysis towards insights" (Pinnell et al. 2017, 129) in a process that departs from traditional methodological considerations. Pinnell et al. emphasize that *insights* are the goal of the investigation, rather than posing questions in advance, and that analytical processes act like tools rather than methods. Furthermore, they argue that analytics, then, requires real-time analysis, with Adejo and Connolly (2017) suggesting that approximately 80 percent of educational data is unstructured, which requires a significant time investment to process and normalize. The capacity of learning analytics to monitor and analyze student behaviors in library learning systems in order to align the library with student learning outcomes and broader institutional goals represents "a 'significant turn' in assessment and evaluation. The shift from studying student experience in libraries to student achievement reflects contemporary pressures on higher education institutions, according to the Association of College and Research Libraries" (Jones and Salo 2018, 308). This shift highlights another potential tension between learning analytics and the values and core competencies of LIS.

Importantly, research carried out by members of postsecondary institutions are governed by, and must comply with, institutional research ethics boards, funding agencies, national or federal regulations, and other bodies. In terms of learning analytics, issues of informed consent, privacy, and confidentiality have been discussed, but less attention has been paid to the question of data retention. For researchers under the aegis of higher education institutions, data retention and disposal are issues that must be addressed prior to data collection. For librarians and information professionals, data retention relates to research data management, their own research projects, and information ethics. Blanchette and Johnson (2002) noted that modern information systems were able to capture and retain user data for infinite periods of time, and they called for the development of policies regarding data retention and disposal. At the same time, libraries have historically followed short-term data-retention strategies in

order to protect patron privacy (Zimmer 2013, 2014). With the rise of Internet surveillance, ongoing consumer tracking (Martin 2016), and the right to be forgotten (Wyber 2018), issues about data retention have been brought to the fore. Furthermore, Hoffman, Lutz, and Ranzini theorize the concept of the "privacy paradox," which refers to the discrepancy between users' strong concerns regarding online privacy and data protection with their actual privacy-protection behavior. The privacy paradox is predicated on "privacy cynicism"—"an attitude of uncertainty, powerlessness and mistrust towards the handling of personal data by online services, rendering privacy protection behavior subjectively futile" (2016, para. 4). Understanding users' perceptions of privacy and expectations regarding data retention is important for libraries and for postsecondary institutions if they are to be trusted by their users, and if they want to differentiate themselves from commercial enterprises such as Facebook and Google.

Conversely, because big data tracks actual learner behavior, learning analytics may be particularly helpful in delineating the differences between self-reported behavioral data, i.e., how people think they behave, and how they actually behave (Vitak 2017). Other ways to align library values and research core competencies and learning analytics might include creating "opportunities to share and hone practices in ways that aggregate *just the right amount of data*, not *all the data* as a default" (Jones and LeClere 2018, 367 [emphasis in the original]). Or as Dishon (2017) and Hoel and Chen (2018) suggest, developing a participatory action-research framework with students, which might include engaging in transparent dialogue about institutional use of student data, involving learners in the learning analytics enterprise through participation in data analysis, and student reflection on their own learning. An example of an initiative aimed at librarians, funded by the Institute of Museum and Library Services (IMLS), is a project to develop field guides for librarians on data privacy and security (Landgraf 2018); the project has produced a final report entitled *Library Values and Privacy in our National Digital Strategies: Field Guides, Convenings, and Conversations* (Zimmer and Tijerina 2018). These ideas and developments provide critical opportunities for institutional members, including librarians and students, to engage with, actively participate in, and potentially exercise agency in, how data are used (Slade and Prinsloo 2013). Determining the role and use of learning analytics in higher education and the position of academic libraries is pressing. In 2018, the ACRL Research Planning and Review Committee (2018) cited "learning analytics, data collection, and ethical concerns" as one of the top trends in academic libraries for the year. The advent and use of learning analytics in higher education and academic libraries highlights the importance of continuing education for librarians and institutional support for library-related research in order to contextualize the limitations and potential use of learning analytics in libraries.

CONCLUSION

The issues raised in this paper about the potential and real conflicts between learning analytics in higher education and librarianship in terms of values and core competencies invite a discussion about what this implies for LIS education. Learning analytics—as defined earlier, "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" (Conole et al. 2011, i)—highlights two important activities. First, learning analytics is about *training* in how to use these technologies and tools to measure, collect, analyze, and report data. Second, learning analytics is about *application* to optimize learning, which may come in the form of an intervention, for example. Neither of these activities are about *education*, which is not only underpinned by the rigor of theory and philosophy, but also aims to develop social consciousness and critical thinking and acknowledges the importance of experience and experiential learning. Two of the primary purposes of LIS education are to critique and question the use of technologies and tools, and to develop social consciousness in the library and information professions, particularly with reference to ALA values, ethics, and core competencies. How does learning analytics align with ALA's *Code of Ethics*? How does learning analytics align with the transcendent values of democracy, the public good, and intellectual freedom and social responsibility? This paper has outlined some of these inherent tensions.

While undoubtedly educational technology can have positive impacts on education and learning, learning analytics privileges the individual over the social, the virtual environment over the physical; can remove us physically, psychically, and socially from one another; and undermines our search for meaning in activities that are embodied, such as learning. While learning analytics proponents would perhaps argue that the purpose of learning analytics is to generate insight into local contexts, populations, and institutions, local insight depends upon the assumption that learning analytics can tell us something of value about the complex and universal process of learning. Learning analytics in libraries compels academic librarians to reconsider professional values and ethics, professional practice, and the ways in which these inform research and assessment and evaluation activities. Academic libraries have a long history of collecting data that was used in-house for a variety of purposes, but as Jones and Salo (2018) note, the shift from using these data to understand student experiences in the library to using these data to support student learning outcomes as designated by higher education institutions represents a significant change. Learning analytics can be conceived of as new and novel because these technologies prioritize some of the current values of higher education, such as cost efficiency and student completion rates. However, concerns have been raised about the ways in which learning

analytics potentially conflicts with transcendent values found in education and librarianship, such as lifelong learning, democracy, privacy, and the rights and responsibilities of citizenship.

Acknowledgment

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