



Transparency and Consent: Student Perspectives on Educational Data Analytics Scenarios

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abstract: Higher education data mining and analytics, like learning analytics, may improve learning experiences and outcomes. However, such practices are rife with student privacy concerns and other ethics issues. It is crucial that student privacy expectations and preferences are considered in the design of educational data analytics. This study forefronts the student perspective by researching three unique futurized scenarios rooted in real-life systems and practices. Findings highlight student acceptance of data mining and analytics with particular limitations, namely transparency about analytics and consent mechanisms. Without such limitations, institutions risk losing their students' trust.

Introduction

As educational technologies evolve, higher education institutions increasingly pursue insights from learning analytics technologies and practices. Some define learning analytics as an area of technology-enhanced learning,¹ while others position it as something less educationally oriented and more akin to a new development in data-driven decision-making.² This push-and-pull between educational and administrative uses of learning analytics is evident in the most common definition of this sociotechnical practice: "Learning analytics is the measurement, collection, analysis, and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and the environments in which it occurs."³ Higher education institutions may collect student data and analyze them for improving learning outcomes,

portal: Libraries and the Academy, Vol. 23, No. 3 (2023), pp. 485–515.

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but it is just as true that they may also pursue learning analytics to “optimize” or use fewer resources in an attempt to cut costs and enact structural reforms, in the name of managing large, bureaucratic, and politically complex institutions.

The key resource in learning analytics is student data. Student data need not be personally identifiable, but the more granular and identifiable the data, the more analytic opportunities emerge. Higher education institutions suggest there is value in creating large, detailed, aggregated data sets. In fact, many universities have invested significant resources in developing data warehouses containing personal, financial, and academic student data, student communications, data gleaned from student interactions with digital sensors on campus, and virtually any other form of data generated at, shared with, or purchased by the university. Higher education institutions claim that these data sets enable them to develop educational and behavioral interventions that are statistically powerful when the sample data set is large and that may be impactful when tailored to a specific student. Beyond personalized interventions, higher education institutions can use large-scale data sets to analyze how subgroups of students engage with campus resources, peers, and even the built environment. They often claim their findings lead to improvements in campus programming, the creation of more engaging social and educational spaces, or the ability to manage labor in less resource-intensive ways.

A variety of institutional actors seek insights derived from student data. Campus administrators want to find financial efficiencies, better allocate resources, and look for ways to demonstrate the impact of student support services. Advisers with expanded access to sensitive data sets and to advising analytics technologies such as EAB Navigate and Starfish increasingly look for ways to maximize the impact of their work on student success.⁴ Faculty and departments develop learning analytics data dashboards based on student use of the learning management system. These dashboards have grown to include predictive analytics as well as direct intervention, such as e-mail notices and referrals to support services. Higher education vendors and other nonuniversity third parties have vested interests in learning analytics data and may themselves hold sensitive data they leverage through product improvement or development of new systems.⁵ Higher education consortia such as Unizin and the Association of Public and Land-grant Universities work with vendors to compare, benchmark, or aggregate data across institutions with the hope of gaining deeper insights.⁶ While the interest in learning analytics from these groups may differ in intention, they share interests and authority.

The promised benefits of learning analytics are many but vague and, in practice, elusive. More clear-cut is that learning analytics has motivated institutional data mining

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and analytic practices that raise notable student privacy concerns. Lacking any real regulation, higher education institutions aggregate, analyze, and use student data for seemingly innumerable purposes.⁷ As long as data collectors can make a basic justification that the student

data have educational properties, few limitations govern the collection and use of those data within the institution or with outside actors who meet the school official designation



(for example, educational technology vendors). Currently, the extent to which students retain privacy hinges entirely on an institution enacting policies that secure student data and limit their use. But privacy scholars would argue that data security is a poor stand-in for privacy. There are legitimate moral and ethical reasons to restrict collection and use of student data, not to mention respect for the normative expectations of the data subjects.

The empirical research described in this article explores those expectations by centering the student perspective with a focus on three sociotechnical scenarios rooted in real-life practices and technologies involving student data uses, some directly related to learning analytics and others tangential to it. Given academic library involvement in learning analytics practices, the researchers also developed questions that investigate the role of libraries and librarians. The overarching research goal was to explore student reactions to these scenarios with regard to privacy and to determine what students could agree to for a privacy-respecting version of the scenario.

The article begins with a brief literature review concerning learning analytics and educational data mining more broadly, especially related to the scenarios. Next follows a description of the research methods, which blended reflexive governance strategies rooted in science and technology studies with online focus groups. Qualitative findings lay out student reactions to the scenarios regarding privacy and trust, as well as dominant themes concerning transparency and consent. The discussion addresses student acceptance of data mining and analytics with particular limitations, institutional responsibility to educate students about analytic practices, and potential costs when institutions lose their students' trust.

Literature Review

Students' Privacy Perceptions and Expectations

Student perspectives on learning analytics initiatives can be critically evaluated against two sets of interrelated expectations: trust and privacy. Trust is a student's willingness to be a vulnerable party in a relationship with the institution and its actors (for example, faculty or librarians). Privacy is defined as a student's right to have identifiable student data collected, stored, and utilized by institutional actors but only for purposes students can reasonably expect. Students trust that their institutions will respect their privacy and not disclose or misuse student data, but instead use student data to serve their interests as information fiduciaries.⁸ Sharon Slade, Paul Prinsloo, and Mohammad Khalil found that 79 percent of their respondents expressed comfort with their institution's access to personal information, which the authors argued translates into a high degree of institutional trust.⁹ Alexander Whitelock-Wainwright, Dragan Gašević, Ricardo Tejeiro, Yi-Shan Tsai, and Kate Bennett concluded from their survey findings that "students

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do place considerable importance on how a university handles their educational data, particularly with regard to controlling who has access to any data and whether consent is required.”¹⁰ Previous studies by a team including many of the researchers on the current article found that, for matters of trust, students drew a strong distinction between nonprofit and for-profit organizations, expressing a much higher degree of trust in their educational institutions than in for-profit corporations, such as social media and e-commerce services.¹¹ The research team declared, “Students put trust in their institution because of a belief that colleges and universities are moral institutions. And because the perception was that universities would not capitalize on student data, they were more willing to share information about themselves for analytic ends.”¹²

The research team also found that students in general trusted their universities and academic libraries not to misuse the data collected about them, and they felt comfortable with institutional access to their data specifically to “improve learning experiences.”¹³ Further survey results indicated that students had reservations regarding librarians accessing or sharing personally identifiable information, but were more trusting of data being used when asked about specific practical applications.¹⁴ When asked if they trusted their university library and librarians to use their personally identifiable information in a way that respected their trust, 72 percent of students said they trusted the library and 70 percent said they trusted librarians.¹⁵

Several recent studies address student perspectives on privacy and learning analytics among undergraduates¹⁶ and graduate students.¹⁷ Many of these studies are Eurocentric, with only Lynne Roberts and her coauthors¹⁸ and Isabel Hilliger and her colleagues¹⁹ studying populations outside Europe. Students in these studies expressed multiple privacy-related concerns, including bias, inaccurate capture of their learning behaviors, increased pressure to perform, negative emotional consequences, and distractions from learning. They consistently expressed a desire for autonomy in making privacy choices and consenting to data collection and use, with at least one study finding that respecting student privacy expectations predicted their willingness to use the tool.²⁰ Additional research with undergraduate students has found that, contrary to arguments that students no longer care about privacy, they express a desire for privacy in relation to learning analytics when given the opportunity.²¹ They not only are aware of privacy-promoting choices but also strategically use the privacy affordances of learning analytics systems.²² Nevertheless, the interviews by the Roberts team suggest that some students think that increased collection of learning analytics data might result in beneficial personalized educational experiences, even as they admit an overall lack of awareness of actual learning analytics practices.²³ Clara Schumacher and Dirk Ifenthaler echo those findings.²⁴

Libraries and Learning Analytics

Library learning analytics includes library-specific data, often in concert with university data, purportedly to enable librarians to identify return-on-investment opportunities, develop strategic partnerships, increase visibility, and demonstrate value to institutional administration.²⁵ Early library learning analytics studies analyzed behavioral data demonstrating student interactions with library services, resources, and spaces²⁶ to correlate library use and services with educational outcomes such as grade point average and retention.²⁷ However, the efficacy of these correlation projects is often limited, with



analysis sometimes leading to statistically significant but unexplainable or low-effect-size correlations.²⁸

As library learning analytics has evolved, more structured and broader projects to engage with data have emerged as collaborations among institutions or library consortia, grant-funded projects, and academic-library vendor initiatives.²⁹ To date, library learning analytics projects have exclusively focused on data gathering and the proposed value of those data to the library as an organization. While anecdotal evidence suggests that libraries use library learning analytics to enhance student learning outcomes, increase library funding for collections or personnel, or connect students with educational resources, the research team knows of no published works that support those claims. Outside the library context, researchers have found little impact on learning and a troubling disconnect with educational theory.³⁰

Library engagement in learning analytics has raised significant information ethics concerns, primarily but not solely along privacy lines. Lynn Silipigni Connaway, William Harvey, Vanessa Kitzie, and Stephanie Mikitish note difficulties in balancing student privacy with potential benefits of analyzing identifiable student data.³¹ Megan Oakleaf recognizes that an inability to address student privacy is an obstacle to larger, more impactful library learning analytics projects.³² Privacy is a contentious issue for librarians more than other professional communities in higher education because of librarianship's deep commitments to library ethics, which Kyle Jones and Dorothea Salo have documented.³³ Oakleaf summarizes, "The inclusion of library data in institutional learning analytics systems requires a significant shift in professional library practice and a reconciliation between long held ethical positions and new imperatives to support student learning and success."³⁴ However, as Carolin Huang, Toni Samek, and Ali Shiri discuss, these emerging analytical and technological techniques involve significant surveillance and may perpetuate or augment social inequality, in stark contrast to professional ethics.³⁵ Notably, librarians often lack institutional power to push back against learning analytics initiatives when they raise ethics concerns.³⁶

Lessons from the Pandemic and the Future of Learning Analytics

The COVID-19 pandemic and the resulting pivot to fully online education highlighted key features of higher education technology. Most of the digital infrastructure, applications, and systems needed to enable this unprecedented shift were in place to support communication, information sharing, and knowledge creation. The existing architecture proved highly extensible to meet new needs and resilient when faced with new pressures, bringing opportunities for technological change, pedagogy, research, and institutional administration. These technologies created a range of descriptive, temporal, spatial, behavioral, biometric, demographic, and other types of data—most of which were identified or reidentifiable—which had the potential to advance learning analytics. The research team identified key themes in learning analytics studies and COVID-19-era initiatives that suggest future applications of data mining and analytic technologies and the ethical issues they create.

First, consider the case of Indiana University–Bloomington and its reaction to COVID-19. Gina Deom, Mark McConahay, Stefano Fiorini, and Linda Shepard used



historical enrollment data and projections combined with social network analyses to determine potential spreader events and plan for course offering modalities, such as online, hybrid, or face-to-face.³⁷ They intend to incorporate housing data in future simulations and further investigate the social network of the students using methods by Uriah Israel, Benjamin Koester, and Timothy McKay.³⁸ Some researchers argued that the significant amounts of data produced as a result of the wholesale move to online learning were worth studying. Jonathan Zimmerman stated that “refusing to do so isn’t just a lost opportunity; it’s a violation of our most sacred trust.”³⁹ Ben Motz, an Indiana University–Bloomington researcher, along with the consortium Unizin, took up Zimmerman’s call and ran a purported “mega-study” that sought to “understand how the transition to remote instruction has affected the learning environment at a massive scale, and how the transition and its impacts might differ for different students and faculty.”⁴⁰ Unizin supports a multi-institutional data warehouse including, among other information, data from the learning management system Canvas. Motz and his colleagues focused on the Canvas data.

As higher education institutions began to bring faculty, staff, and students back to campus, many campuses relied on policies and restrictions, while others adopted new technologies and used their digital architectures to monitor campus movements.⁴¹ At Oakland University in Michigan, on-campus students were required to wear a “BioButton,” a medical device attached to their skin that would “measure their temperature, respiratory rate, and heart rate, and tell them whether they’d been in close contact with a button wearer who’d tested positive for [COVID-19].”⁴² Other higher education institutions, such as Colorado Mesa University in Grand Junction, demanded that students use mobile apps to report symptoms and respond accordingly.⁴³ Albion College in Albion, Michigan, forced its students to use an identity-revealing, real-time location tracking application in the name of COVID-19 tracing.⁴⁴ The *New York Times* reported that “some [higher education institutions] have adapted the ID card swiping systems they use to admit students into dorms, libraries and gyms as tools for tracing potential virus exposures.”⁴⁵

Arguably one of the most prominent—and contentious—developments during the pandemic was higher education’s adoption of test proctoring tools, often embedded into learning management systems.⁴⁶ In lieu of a secure physical test-taking environment,

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educational institutions argued that they needed a way to ensure the academic integrity of their tests. Therefore, they turned to such tools as Respondus’s LockDown Browser and Monitor, Honorlock, Examity, ProctorU, and Proctorio. Some of the systems use artificial intelligence (AI) or a human proctor who surveils the test taker via a webcam to flag suspicious behaviors.⁴⁷ While both approaches raise ethical problems, the AI applications for test proctoring were heavily criticized for producing too many false positives, discriminating against people

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with disabilities, and algorithmic bias.⁴⁸ Backlash to proctoring has led to congressional inquiries,⁴⁹ lawsuits,⁵⁰ and student petitions.⁵¹ Some prominent institutions, including the University of Illinois at Urbana-Champaign, canceled their proctoring contracts.⁵²

Before the COVID-19 pandemic, higher education institutions had already expanded their data mining and analytic capacities and capabilities. Work by Kyle Jones, Alan Rubel, and Ellen LeClere⁵³ and another investigation by Rubel and Jones⁵⁴ documented the growing role of predictive analytics in learning management and advising systems, in addition to consortial efforts to aggregate data across institutions. In 2020, Jones and six other authors of the current article surveyed common and emerging library learning analytics developments.⁵⁵ In a critical analysis of some of these developments, Britt Paris, Rebecca Reynolds, and Catherine McGowan argued that existing institutional policies and vendor contracts demonstrate “egregious shortcomings in surveillance, privacy, and protection of intellectual property.”⁵⁶ In response to COVID-19, some of these data efforts and related problems became supercharged. Institutions clearly have infrastructure in place to collect, analyze, and act on comprehensive data sets while integrating new invasive technologies.

Research Questions

Current research on student perspectives and expectations of their privacy in relation to learning analytics focuses on downstream consequences of current-day technologies and practices. Such research seems unlikely to affect already-designed sociotechnical artifacts or improve student privacy conditions. Jones and Chase McCoy argue that “instead of looking at downstream effects and then shining the proverbial light after the fact, there is a need to look at—and influence—the design of ethically sensitive data technologies and practices closer upstream.”⁵⁷ This research takes up this call by examining plausible sociotechnical scenarios of learning analytics yet to be introduced but with affordances and data flows that are rooted in existing practices, though not necessarily in one tool or system. The scenarios address the following guiding research questions:

1. What expectations do students hold regarding trust and privacy in relation to the scenario?
2. What alterations affect the acceptability of the scenario?
3. What trust and privacy conditions do students agree must be in place for the scenario to be acceptable?

The purpose of asking these questions is to influence emerging types of learning analytics technologies and practices so that student perspectives can be taken into account in design and implementation.

Methods

Futurizing with Sociotechnical Scenarios

The “reflexive governance” methodology frames this research. Reflexive governance enables researchers to systematically inquire into future artifacts, systems, and ways of engaging with technology.⁵⁸ As Clark Miller and Ira Bennett write,



It means assessing the kinds of technological societies we are building, and the political economies that are building them. It means deliberating in depth about the future of technological societies and the potential for human meaning and wellbeing within them. It means identifying not only what gadgets might arise but also how gadgets intersect in society, with one another and with people, how people identify with, make use of, oppose, reject, apply, transform, or ignore various gadgets.⁵⁹

Science and technology researchers often pair futurized scenario focus groups with a reflexive governance framework to assess the acceptability and feasibility of potential technologies. Lauren Keeler, Michael Bernstein, and Cynthia Selin argue that “scenario research methods in particular offer a means of surfacing moralities and values often underlying technological change yet crucially do so in a present-focused modality.”⁶⁰ As members of the current research team write in another publication:

With the right structure, scenarios enable participants to think through design opportunities and dead ends so that the sociotechnical systems respect their individual interests and values, along with those they share with the various communities in which they are embedded. The aim is to establish consensual (re)designs of the scenarios among participants, to shape them for an agreeable, sustainable future, as an act of reflexive governance.⁶¹

The research team iteratively developed three futurized sociotechnical scenarios of learning analytics practices. First, each team member ideated on their own based on their expertise of learning analytics and previous research using a structured worksheet. Second, the team assembled to review individual ideas and select the scenarios most rooted in real applications of learning analytics but with plausible future extensions. Next, the team assessed the emerging scenarios using a virtual card sorting exercise, evaluating them first according to their relation to libraries and participant comprehensibility and then according to their potential benefits and privacy risks. This process allowed the researchers to settle on three plausible scenarios: (1) scenario one, library services provided via the learning management system (LMS); (2) scenario two, the creation of a library data warehouse (LDW); and (3) scenario three, real-time location tracking (TRK). Finally, the researchers divided into subteams to develop each scenario by conducting a literature review for existing applications of similar technologies and outlining technology systems and practices on which the scenario relied. The subteams also outlined the justifications for use, goals, benefits, and privacy harms of their scenario. Subteams ran member checks with students to determine if the scenarios were intelligible; if any issues emerged, the research team made minor edits according to student feedback.

The research team used a slide deck template to guide the focus groups, beginning with research team information, the timeline and structure of the focus group, a review of logistics, including technology checks and recording reminders, and ground rules establishing equitable and respectful conversation. The customized scenario portion of the slide decks laid out each scenario, including a brief description, relevant data sources, and the goals and rationale for each scenario, followed by discussion prompts addressing trust and privacy as explicit themes. For the themes of trust and privacy, the deck included a slide to elicit students’ views on the scenario (“the general question”) and another to introduce scenario changes (“the alterations question”) to further draw



out students' views on trust and privacy issues. A final slide helped build agreement regarding an acceptable use of the future technology that would align with their trust and privacy expectations ("the consensus question"). The research team describes the three scenarios in the Appendix.

Virtual Focus Groups and Data Collection

Researchers originally planned to conduct in-person focus groups at seven research sites: Indiana University–Indianapolis (IUPUI); Indiana University–Bloomington; the University of Illinois at Chicago; Northwestern University in Evanston, Illinois; Brooklyn College, City University of New York (CUNY); the University of Wisconsin–Madison; and the Borough of Manhattan Community College (BMCC), part of CUNY. Due to COVID-19-related limitations, the researchers reconceived the in-person focus groups to conduct them over the Zoom Web-conferencing platform.⁶² The reliance on Zoom across seven institutions with different versions of or levels of access to the platform required a detailed checklist of Zoom settings options to ensure uniformity in how the focus groups were conducted and recorded.⁶³ Further, the complexity of online focus groups required that each session had at least two researchers present to conduct the focus group, take notes, and provide any needed technical assistance.

The research team's pivot to Zoom during the pandemic was possible in the context of the larger move to remote learning across higher education, which meant that students and researchers were already familiar with the platform. While Zoom required more researchers to participate in a single focus group, this was also a significant benefit. Researchers could experience multiple focus groups firsthand before encountering them in the data, which supported reflections in team meetings and increased sensitivity to the data. The ease of recording and remote access, in turn, facilitated integration of the data into the research team's qualitative data analysis software, MAXQDA, and comprehensive review of transcripts that were professionally and confidentially created by Automatic Sync.

Before conducting the focus groups, the research team obtained 3,000 names and e-mail addresses for current undergraduates over 18, stratified by class standing at each institution; these lists were provided by institutional research and registrar offices. Some researchers obtained a second round of student contacts when recruitment stalled. Via Qualtrics, each team member sent their sample a recruitment survey, consent form, and selection of dates and times for a focus group. Recruitment survey reminders were sent out until 8 to 12 students were recruited for each focus group to ensure a minimum of 5 participants for each. In the end, two focus groups ran with only three or four participants each due to last-minute dropouts. Researchers scheduled focus groups from March through May 2021, with one per scenario at each institution, for a total of 21 focus groups and 116 undergraduate student participants.

Research Ethics

Given the sensitivity around research ethics in library learning analytics projects and published research,⁶⁴ and considering the study's focus on privacy, the team carefully designed and conducted this research to highlight and attend to research ethics concerns.



The team discussed at length the potential harms and benefits of collecting participant demographics and chose not to gather the information because it would have added only minimal analytical value while increasing the potential for reidentification harms. The research team will destroy potentially identifying video data (from which some demographic information could be inferred) after the project's completion. Other identifying data, including recruitment lists, have already been destroyed.

As this research team has discussed in another publication,⁶⁵ the use of Zoom introduced privacy concerns that were addressed in the research protocol. About the process, Kyle Jones, Michael Perry, and Mariana Regalado write:

We attempted (successfully) to limit these issues by developing a comprehensive checklist protocol to ensure that all the settings were appropriate and consistent across groups. We developed the protocol by looking at every Zoom setting and determining the best options for ensuring a smooth process and enhancing privacy protections. Some of these choices included: not allowing students to rename themselves, using the waiting room, muting participants as they joined, deactivating chat, instructing students and researchers to blur their backgrounds, and, among other things, recording to the computer rather than the cloud so we could maintain control of the recordings.⁶⁶

Further, the research team changed usernames to pseudonyms (such as Participant 1, Participant 2, and so on) before recording began. They referred to participants during sessions only by those pseudonyms to further protect them in research data, such as video, audio, and transcripts.

Each team member clearly and deliberately documented all research recruitment processes, communications, protocols, and privacy-protecting efforts, including data management strategies (such as data security and retention schedules).⁶⁷ All documentation was sent to the respective institutional review boards for review; the research was approved at all institutions and classified as exempt.

Data Analysis and Research Quality Checks

Data analysis included multiple phases. First, the researchers imported the transcripts into MAXQDA and used the focus groups tool to automatically code each participant's speech as text.⁶⁸ Next, the researchers conducted the following coding strategies: sectional coding, content coding, textual autocoding, and thematic coding. Sectional coding focused on dividing each transcript into segments according to areas of the focus group, including the themes (privacy and trust) and the question types (the general question, the alterations question, and the consensus building question). In combination with the autocoded participant speech as text, sectional coding enabled the research team to home in on areas of the focus groups during the following phases of analysis. Next, the researchers adapted the codebook developed for the interview phase to meet content coding needs for subsequent phases.⁶⁹ Research team members coded all transcripts and examined the frequencies of words used by participants throughout the transcripts. Relevant words were sorted into 25 categories to create a dictionary of terms, which was then used to autocode the transcripts.⁷⁰ Finally, the researchers concluded coding by developing in vivo and theoretically oriented inductive codes. This process was supported by running ad hoc code co-occurrence and combination analyses, word and



code frequency modeling, and lexical searching to develop new insights and support emergent findings.

The research team pursued evaluative criteria for this project that aligns with their previous student privacy research,⁷¹ emphasizing credibility, trustworthiness, dependability, and authenticity.⁷² The team attempted to design a rigorous qualitative study with a clear logic line supported by detailed methods and an audit trail of documentation that can support the wide transferability of findings. Over years of collaborative research, the team members have discussed inherent biases and interests known to one another to informally catalog them and ensure, to the extent possible, that they do not influence the team's research designs and analyses or bias research participants.⁷³ The research team acknowledges that their interest in student privacy—and in establishing privacy protections—drives their work on behalf of students who are rarely allowed to make privacy-protecting decisions for themselves. But the team's efforts to be transparent about their subjectivity have enabled them to stay focused on student perspectives and expectations of privacy in this and other related projects.

Findings

Acceptability of Scenarios

LMS: Library Resources and Services in the Learning Management System

In reaction to the general question eliciting students' views on the scenario of library services provided via an LMS, more coded segments signaled approval (N = 105 segments) than disapproval (N = 75 segments). Students characterized this data practice as clearly oriented with educational needs and as a way to "improve students' experiences," as a Brooklyn College student put it. Further, participants stated that analyzing student data as they exist in a learning management system and in relation to library resources and services aligned with strategies to improve library practices. A student from Indiana University–Bloomington expressed the general response to this scenario:

I think it makes it more understandable what information students are using and where they are better spending their time when

it comes to resources that the library provides. So when it comes to them using it [to develop a] better understanding of their student population and the information that they use, I think that's completely valid, and I'm, like, fine with that in my opinion.

There was a clear understanding of how analyzing learning management systems and connected data could aid students and improve library practices.

Similarly, a participant at IUPUI responded to the scenario by stating, "It says that their main goals are, like, to help students and to help librarians as well as the long run. So, like, my kind of view on it is, like, 'Why not?'" There was a clear understanding of how analyzing learning management systems and connected data could aid students and improve library practices.

*LDW: Library Data Warehouses*

In reaction to the general question asking students' views on the creation of a library data warehouse, there was less approval (N = 81 segments) than disapproval (N = 96 segments). This decline in approval compared with the scenario of library services provided via a learning management system tracks to the differences in the nature and scope of the data collection. This scenario includes more data sources and more granular data; it also starts by positing identifiable students and institutional actors who share and analyze the data broadly. Students could see logic behind the data collection as a way of better allocating resources and improving library services or collections, but they often had concerns, especially regarding the sharing of data. As a student from Northwestern University said:

Like, if they collected the data and then could say that they were going to use what they learned from that to, like, make improvements in specific ways, I think I would trust that. And if the plan for improvements was to be shared with other universities, like, generally without identifiable data, I would trust that. But if it was just turning over all data collected without, like, a specific reason for it, then I don't think I would trust that.

This opinion highlights the common desire students expressed for clear, specific goals for data use. General statements about improving learning or experience were not sufficient to justify the data collection. This condition also held true for sharing the data; students desired a specific reason for it.

TRK: Location Tracking

The data indicate even more disapproval for the real-time tracking scenario than the other scenarios. Students expressed disapproval in 110 segments, compared to approval in 85 segments. Notably, no Northwestern University students indicated approval when asked to respond generally to whether the scenario respected their trust and privacy, a significant finding in and of itself that this article discusses later. Where approvals for the scenario did exist, they were associated with three primary sentiments. First, students indicated a belief that institutions would conduct such tracking with good intentions. Second, tracking and analyzing student movements could potentially improve the institution's support of educational initiatives, including finding opportunities to make institutional practices more efficient. Finally, tracking could enhance student safety by using data to investigate misconduct and criminal activity. Northwestern students expressed great concern about sharing any kind of data with police, citing local examples of police using university-provided location data to target individuals, as well as the ability of police to use other methods to obtain these data. Other students were more open to the possibility of location tracking. One participant from the Borough of Manhattan Community College said, for instance:

I feel like as long as there's, like, transparency with, like, maybe who the university would be sharing it to, that would be cool . . . When you first brought up, like, geographic location, I was like, oh my God . . . it, like, gave me the vibes of, like, redlining . . . So I feel, like, if it's just, like, on the campus, that's cool.



Students once again clearly stated their expectations that the kind of data collected and their use should be made available to them. For instance, one student from IUPUI explained, “So I think if the university is going to do this, everything needs to be explicitly stated on what’s being collected, what it’s being used for, and who it’s being shared to.” Further discussion of these expectations takes place in the section “Transparent Educational Purposes.”

Scenario Privacy and Trust Responses

LMS: Library Resources and Services in the Learning Management System

The acceptance of this scenario tracked with the belief that it respects student privacy protections and maintains their trust in the library and the institution. Students found few reasons for concern about their privacy as it relates to libraries and library uses of student data. As one Indiana University–Bloomington student said, “It’s never become a problem,” adding, “The library and the university respect my privacy enough.” But privacy concerns could increase and students’ trust could decrease given specific events or changes in the scenario.

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Students felt that institutions respected their privacy expectations when the institutions focused their use of data and analytics on education, made their practices transparent, and deidentified all data, the default condition in the scenario. Importantly, students clearly trusted librarians more than faculty, because they perceived librarians as less powerful and unable to affect their educational success for good or ill. Put differently, librarians who acted on the data within the scenario, students believed, could not impact their grades or influence other important academic decisions. Of seemingly greatest concern to the students was the role third parties might play. Expressing the core of this theme, a Northwestern University student had this to say:

Most people seem to believe the library and the university will genuinely have their best interests in mind; I’m of the same opinion. But once you start involving third parties, that’s when things start getting a little more questionable and the motives get muddled, and inevitably it might be more for monetary sorts of gains as opposed to, like, you know, research and bettering the services for the students.

Students were dubious that companies intend to protect their data and use the information solely for educational purposes—even when the scenario did not explicitly address third parties beyond the LMS company.

LDW: Library Data Warehouses

Overwhelmingly, students expressed a clear sense of trust in libraries and declared that librarians cared about students and their learning. They also saw ways a data warehouse could inform and support the library in this mission. Students did find the potential



purposes for the data warehouse to be overly broad and lacking in justification. They also questioned the necessity of such data collection and why other less intrusive methods

Overwhelmingly, students expressed a clear sense of trust in libraries and declared that librarians cared about students and their learning.

were not used. As one student from the University of Illinois at Chicago put it:

I would probably be a little more trustful if we were now unidentifiable . . . I think there are other ways, like you can always send out surveys and

things to . . . collect research and information about the demographics of, like, the types of students a university has, which would still be fairly accurate and can be used to, like, accomplish those administrative and educational purposes where you don't need to be monitoring students, like, every single move.

Students found data sharing and broad access to the data warehouse to be problematic and not in alignment with a process that respected their privacy. Several students felt any data sharing should be disclosed to them. As one from the University of Wisconsin–Madison said, “Like, how we got a privacy form regarding this study [the study’s consent form], I think something that the library could do would be, like, [explaining] who we would be sharing it with to make people more aware of where their information is going.”

Students also shared concerns about the identifiability and granularity of these data and the possible effect a data breach or hack could have. The alterations to the scenario (making the data unidentifiable instead of identifiable) eased some of the concerns, as did limiting the sharing of data.

TRK: Location Tracking

Students once again displayed a sense of trust in their institution regarding the collection of geographic location data, with Northwestern University as the stark exception. This trust did not diminish the sense that location data collection had a negative impact on an individual’s privacy. Students expressed a clear desire that this information be deidentified, but some acknowledged that it would be easy to reidentify students based on patterns in the data. A participant from the University of Illinois at Chicago explained, “Considering that technically, if you really had the time and the effort, you could still piece together what a student’s life was like; you just have to jump through a couple of social engineering hoops to do that.”

This scenario raised an interesting friction point. While there was noticeable negative sentiment toward the scenario where both privacy (N = 139 segments) and trust (N = 139 segments) were concerned, the data also signaled notable approval where trust (N = 172 segments) was concerned. This disconnect seems to demonstrate the clear struggle this scenario poses, but it also indicates willingness to come up with conditions that made the scenario trustworthy. For example, students expressed ambivalence about the use of data by governments and law enforcement, noting the potential need to address issues of public safety while also expressing concern these practices could easily result in overreach and violations of their privacy.



Transparent Educational Purposes

Students across all scenarios at all institutions generally agreed with the baseline purposes of the stated scenarios, which were all ostensibly educational goals and rationales. Both the scenario of services provided via a learning management system and that of creating a library data warehouse had as explicit goals the improvement of library services and resources to support students' academic success. The location tracking scenario had broader objectives, including both improvement of university services and resources as well as assessment of space use. As a student from Indiana University–Bloomington articulated about the real-time tracking scenario, "I feel like if the data is used as a way to benefit the university, I don't have a problem." Students across the scenarios agreed that the goals of data collection might benefit them directly or acknowledged that data collection for educational purposes could help others.

At the same time, in their discussions around alterations and consensus building, students articulated a number of conditions they would need to feel comfortable with use of their data for educational purposes. The requirement expressed most often was that the data collected on them be unidentifiable. It is important to note also that students in the location tracking focus groups

were more concerned about identifiability and skeptical about anonymization than those discussing the other two scenarios. Students articulated a strong preference that personally identifiable information

Students articulated a strong preference that personally identifiable information not be collected

not be collected and asserted that when scenario agents gathered personally identifiable information, those agents should deidentify the data and impose strict limits on who could view it. For example, some noted that they could see a benefit for faculty to have access to their data but would not want the data to impact their grades. Some students in the focus groups discussing services provided via a learning management system also did not want their instructors to penalize them for their patterns of access, explaining that the time spent logged into the learning management system was not necessarily the only time they spent on their coursework. In a few focus groups, students came to the consensus that personal information should not be kept after students leave the institution. A participant from the University of Illinois at Chicago (UIC) explained about the real-time tracking scenario,

I get that during the time at UIC yes, okay . . . each individual's data should be kept. But after their time with UIC, I think then that data should then just become aggregate because you know every year there's going to be new students . . . Not, like, hold on to previous students' data for, like, 10 years, you know?

Students made clear that they only wanted their data to be collected with an explicit plan for use (as indicated in the section "Location Tracking") and that they wanted to know specifically how gathered data were being used to improve the student experience. One focus group for the scenario of services provided via the LMS articulated strongly that potential benefits of the data collection would be appealing to students if they were educated about them. An IUPUI participant commented,



Potentially seeing how our contribution is actually helping. Because like these improvements happen, but can they, like, specifically tell us, like, what caused a certain change. Like, let's say, if they made the library that we currently have more easy to use, and to say, "Well, this type of data helped us develop this," instead of just saying, "We updated," [without] context.

Overall, most students were open to a use case for data collection and sharing within their institution that involved making improvements either in their own educational

... students were particularly concerned about the potential use of data for targeted advertising or marketing, which was viewed almost universally negatively.

experience or that of their fellow students, as long as the institution was transparent with what data were collected, who had access to them, and how long the data were retained. This view extended to the use of data by third parties external to the institution, where students only approved use cases in narrow instances where data might be used to improve resources available to them. In these

cases, students were particularly concerned about the potential use of data for targeted advertising or marketing, which was viewed almost universally negatively. Moreover, they objected to any form of data sales to third parties as a violation of their trust.

Expectations for Consent

While many students articulated an understanding that they or others might benefit individually from the collection of their personal information, possibly in the form of recommendations for sources from the library or safety in buildings, across all focus groups they overwhelmingly felt that students should be given the choice to consent or refuse data collection (N = 335 segments). There were slightly more mentions of consent in the library data warehouse and real-time tracking scenarios than in the LMS scenario. Consent was frequently referred to in concert with questions of trust, both how consent could increase or decrease trust (if no consent option was provided). Further, students expressed that a lack of consent options signaled to them that the institution did not respect them. Participants commonly believed they deserve information and education about proposed uses of their data (N = 85 segments), including the purpose of data collection and use, and information about how use of their data directly benefited them. While consent and the ability to refuse it were a requirement for all participants, those in two focus groups noted that too many students opting out of data collection could damage the ability of the library or university to collect potentially useful information.

Students wanted to be asked for their consent early and often, but opinions about consent logistics were highly diverse (N = 65 segments). Most agreed that information

Students wanted to be asked for their consent early and often . . .

about data collection and use was important at matriculation. Some also wished to be reformed once per year, once per semester, or even at each new use of their data. There was broad agreement that information and consent forms should be as brief and comprehensible as



possible rather than phrased legalistically. A little under half of mentions of authorizing data collection and use (N = 31 segments) said that consent should be opt-in, while a slight majority (N = 34 segments) was content with opt-out. Several respondents (N = 23 segments) believed that students should be able to change their consent decisions, and an argument arose from a few (N = 10 segments) that no university-provided student services should be predicated on consent, much less degraded because of a decision to withhold consent. Suggestions for accomplishing information and education included e-mail, pop-up messages, and specific consent web pages. Finally, students expressed a desire for transparency in how data about them would be accessed and used. As one Northwestern University student explained about the location tracking scenario, "I want to see exactly what they can see with that data and what they can do with it. I want to be able to see everything a police agency can see about myself. There should be no difference in how that data is seen by them versus me."

Discussion

Acceptance of Data Mining and Analytics

The research team's design of three dissimilar futurized scenarios was purposeful. It enabled the study of varied information flows, purposes, and access by institutional actors. Across all three scenarios, the results show that students generally accepted their institution's access and use of their data for library and other educational purposes, consistent with prior research.⁷⁴ This acceptance was due in part to the trust they had in their institutions. To some stakeholders in higher education, this acceptance of data mining and analytics may be unsettling. To others, the findings may provide more latitude to advance learning analytics practices. This empirical evidence refutes the perception that students are unwilling to accept learning analytics practices. But three important points about this general finding add further nuance to extant research arguing that students do, in fact, care about their privacy.⁷⁵ First, they place specific limits on data mining and analytics, which they expressed in the consensus section of each scenario. Second, students know little about the potential privacy and other harms brought about by data mining and analytics, which requires institutional actors to be transparent about their practices and to educate students responsibly on risks and threats. Finally, there are genuine costs associated with losing student trust because of invasions of privacy, which the research team has seen play out in real life. All three points are addressed in the following sections.

... students generally accepted their institution's access and use of their data for library and other educational purposes

Limits on Data Mining and Analytics

Students articulated a fairly narrow definition of educational purposes: data should be used only to improve their own educational experience or performance. Students rarely approved of broader—but often routine—institutional uses of data that might contribute to education generally, such as benchmarking, tracking performance indicators, or im-



Students rarely approved of broader—but often routine—institutional uses of data that might contribute to education generally, such as benchmarking, tracking performance indicators, or improving software systems.

proving software systems. This misalignment between what students understand as appropriate use of their data and how institutional actors understand data use creates potential for conflict once students become aware of and respond to what they perceive as institutional overreach.

Provisions of the *Family Educational Rights and Privacy Act (FERPA)*

governing use of student data are poorly designed to address data access and use concerns. FERPA regulations allow for broad classification of third parties as entities having “legitimate educational interest” for use of student data, effectively creating more avenues for uses that students find problematic.⁷⁶ Moreover, the data collection and use practices of vendors and publishers with whom libraries contract frequently conflict with student desires not to be “watched” and for third parties not to commodify their data.

Given the constraints students want on the use of data about their performance, initiatives such as the ManyClasses Project⁷⁷ and Terracotta,⁷⁸ which seek to utilize large LMS data sets to identify best practices in teaching and learning, must be careful to incorporate disclosure and consent practices to avoid violating students’ trust. The first ManyClasses project examining the effects of the timing of feedback on assignments exemplifies responsible practice by obtaining explicit consent and FERPA waivers for access to course data.⁷⁹ With a 79.9 percent participation rate, this study also demonstrates the practical efficacy of disclosure and consent for learning analytics analyses.⁸⁰

Educating Students about Data Practices and Seeking Consent

Students across all focus groups generally agreed that data collected in each of these scenarios could be used for educational purposes, within the conditions stated earlier—conditions that tightly align with previously published research.⁸¹ However, it was clear that students lacked important knowledge about data systems: their stated wishes for services were sometimes at odds with their apparent privacy preferences. For example, many interventions that a library or institution might propose within the broad category of educational purposes—recommending specific library resources or academic services—would likely require collecting personally identifiable information without deidentification. Similarly, many participants expressed a strong preference that the library and university not share their data with third parties, which is in tension with the reality that academic institutions rely on systems they purchase or license from third parties.

The underlying sentiment that students expressed was a fundamental desire to have agency in their own educational process. Overall, higher education institutions have historically not engaged students in gaining their consent for data collection and use. Institutions therefore need to carry out systematic privacy education rather than rely on a student’s lived experience for understanding complicated data flows, uses, and pri-



vacy problems. Awareness has increased since 2020 in part because of pandemic-driven adoption of proctoring software and its obvious surveillance and other ethical problems. Yet, focus-group findings indicate that students would still benefit greatly from data privacy education, especially concerning how their institution uses their data, to resolve some of the identified contradictions. Participants across all scenarios articulated their desire for purposeful consent mechanisms governing collection and use of their personally identifiable information. Another mode of education could be discussion-based; in most focus groups, students pointed out to one another contingencies and threats and shared their experiences with surveillance. Such sharing created organic learning. Academic libraries, as both a site of institutionally owned academic technology and licensed technology from vendors, are well-located to educate students about consent during their college careers.

. . . many participants expressed a strong preference that the library and university not share their data with third parties, which is in tension with the reality that academic institutions rely on systems they purchase or license from third parties.

The Cost of Lost Trust

One critical concern this research documented is the loss of trust in colleges and universities that can follow when students feel institutions violate their privacy or break their trust. Two cases highlight this possible consequence: use of location tracking tools by George Washington University in Washington, D.C., and by Northwestern University.

George Washington University implemented a location tracking system using Wi-Fi data aggregated into the Degree Analytics system “to determine density and use of buildings by students, faculty, and staff [to] inform the Safety and Facilities team’s operational priorities.” The university did so, however, without fully disclosing the tracking to students or seeking their consent.⁸² When university departments and offices were asked if they wanted to use the data, Suzanne Smalley reported, “The registrar’s office declined and said the data is not useful, the libraries declined and said the data is not useful and added that collection of this data was unethical, several deans were furious when they found out about this effort . . . everybody on the academic side was immediately noticing how damaging that was and how fraught this was,” including faculty department chairs. Nevertheless, the university’s compliance division and general counsel allowed the system to be developed and piloted.⁸³ Isha Trivedi, the reporter who broke the initial story, said that students expressed surprise and thought it should not have happened without a clear justification.⁸⁴ As this case showed, if administrators wish to continue using large-scale data collection as a means of understanding students, they must be aware of the potential it has to exacerbate issues of institutional mistrust. Similarly, the use of data for purposes beyond educational understanding must be done thoughtfully, knowing that the impact of such use may go far beyond the specific context of that situation.



... if administrators wish to continue using large-scale data collection as a means of understanding students, they must be aware of the potential it has to exacerbate issues of institutional mistrust.

The absence of any approval in the Northwestern University geographic location tracking scenario was underscored by participants who cited the university's punitive response to students who protested a speech by former Attorney General Jeff Sessions

in 2019 as the reason for their disapproval and lack of trust in the university.⁸⁵ Northwestern University students believed that university police used photos of protesting students in the student newspaper, *The Daily Northwestern*, to identify and bring criminal charges against some protesters, and they understood that geographical tracking data could be similarly abused. This fear of retaliation and the understanding that data may be used to identify students remain an issue; student demands to abolish the Northwest-

ern University Police grew in 2020 and 2021.⁸⁶ This event has also shaped the experience of international students, who are subject to additional rules. One Northwestern University focus group participant said that they worried they would inadvertently be viewed as part of a protest, since it would violate the terms of their visa. The thought of the university collecting geographic location data in an identifiable fashion was a great concern, especially the threat of it being interpreted to show participation in a protest. Northwestern University's history responding to student protesters cannot be divorced from any efforts it makes in utilizing data for educational purposes; students aware of this history responded to scenarios about data collection with skepticism and an overall lack of trust that the institution would not use the data for disciplinary or other punitive purposes.

When asked to develop a consensus around privacy and trust related to the geographic location tracking scenario, Northwestern University students discussing the scenario almost immediately brought up the need for governmental regulation of student data. They had little faith in the institution's ability to govern itself and felt it needed outside pressure to be accountable. The loss of institutional trust in this situation impacts not only student faith in the use of data for educational purposes but also the ability of the institution to present itself as information fiduciaries working in the best interests of students. As more surveillance-based educational technologies, such as online proctoring, are implemented, this trust may erode without institutional transparency and binding consent mechanisms.

Conclusions and Recommendations

The research team conducted 21 focus groups spread across eight institutions to gather student perspectives on issues of trust and privacy to inform the development of learning analytics and library learning analytics technologies and practices. The findings indicate general acceptance of a broad array of data flows and practices in support of learning analytics and more general educational data mining practices. But acceptance is conditioned on real limitations and requirements:



1. Students want institutions to use student data solely to improve their educational experience or performance.
2. Students need education about data practices and related privacy and ethics issues; informed consent mechanisms can support these needs.
3. Students who feel their privacy is violated and their trust is broken because of a specific data practice will likely regard their institution and all its data practices negatively going forward.

Institutions have significant ethical responsibilities attached to any learning analytics or other educational data mining practice if they wish to maintain a cordial, trustworthy relationship with students. The findings support Paris, Reynolds, and McGowan's policy recommendations in light of troubling educational technology initiatives and the likely trajectory of future invasive and ethically suspect tools and practices.⁸⁷ First, Paris and her

coauthors recommend, based on empirical research, that "independent data privacy and protection boards" be established; the team emphasizes that such boards need authentic student representation. Second, institutions should adopt "opt-in informed consent for all participants and platforms." Requiring opt-in consent cre-

ates significant practical and technological concerns; the findings do suggest that aiming for opt-in as a guiding principle is worth attempting as a starting point for informed consent. Third, institutional actors should take "a courageous stance to ending state and corporate surveillance of students." The team believes that such surveillance puts student trust at risk and might deleteriously affect an institution's reputation. Finally, institutions should seek "public subsidies" to establish "research-based design work in educational technology to create small-scale, cooperative, open-source educational tools." The obvious benefits of such initiatives include local control of data and the possibility for ethically sensitive technologies, along with codesigning educational data mining and learning analytics tools alongside students in accordance with their privacy expectations and preferences.

As with any research project, this one entails limitations. First, focus groups are sometimes limited by "dominant voices," individual participants who seek to control and steer the conversation. The research team was aware of this risk before running the focus groups and strategically called on all individuals to the extent possible to limit this effect. Second, participants may feel encouraged or required to match their responses to the emerging norm. However, the scenario slide decks specifically promoted diverse and differing points of view, and the consensus section of each scenario required each participant to engage in a constructive conversation with their peers. Even though the research team attended to these issues, they still may have occurred in limited form.

Practitioners, including librarians, advisers, instructional designers, instructional faculty, and researchers, should prioritize student perspectives and expectations of privacy in their design and use of educational analytics. The scenarios discussed in this study are feasibly replicable using a similar multi-institution design or within a single institution,

... aiming for opt-in as a guiding principle is worth attempting as a starting point for informed consent.

This manuscript is under review for publication. Accepted for publication on 23.3.



and the team has fully documented its research artifacts (for example, protocols and communications). The research design is also extensible. Other researchers and practitioners

Practitioners, including librarians, advisers, instructional designers, instructional faculty, and researchers, should prioritize student perspectives and expectations of privacy in their design and use of educational analytics.

could modify the scenarios with present-day or futurized learning analytics, library learning analytics, or other educational data mining practices to evaluate student perceptions of these projects and ensure ethical congruence with their expectations.

Acknowledgments

This project was made possible in part by the Institute of Museum and Library Services (LG-96-18-0044-18). The views, findings, conclusions, or recommendations expressed do not necessarily represent those of the Institute of Museum and Library Services. The team thanks its research assistants for their support: Amy Martin, IUPUI; Arudi Masinjila, Northwestern University; Margaret McLaughlin, Indiana University–Bloomington; and Claudia Wald, CUNY. Finally, the team thanks the undergraduate students who volunteered their time to participate in this study.

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Appendix

Scenarios

Scenario one: Embedding library resources and services in a learning management system (LMS)	Scenario two: Library data warehouses (LDW)	Scenario three: Location tracking (TRK)
Brief narrative description		
<p>Your university library is planning to integrate library services and resources into the learning management system, Canvas or Blackboard. This means data about your use of library services and resources through Canvas or Blackboard will be collected and made accessible for analysis purposes.</p>	<p>Your university library is planning to centralize student data from across the different libraries and library departments into a single collection of data called a “library data warehouse.” This enables librarians to know what library resources and services identifiable students are using. It also allows them to combine library data with other data, such as academic records or student profile information, for analytical purposes.</p>	<p>Your university has started using a system that compiles and organizes geolocation data. The system enables its users to know the past locations of identifiable students. The university may combine geolocation data with other student data (e.g., academic performance data) for analysis.</p>
Data sources		
<p>Interactions in the learning management system, with third party tools or library resources embedded in the learning management system.</p>	<p>Interactions in the learning management system, authentication logs for electronic resources, ID card usage, study room and event registrations; log-ins to campus computers and campus Wi-Fi, including location.</p>	<p>Log-ins to campus computers, campus Wi-Fi, and the university/college mobile app, and ID card usage.</p>

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Data collected		
Collected data included time-on-page tracking, communications, submitted assignments, grades, and library materials or equipment looked at, downloaded, or checked out.	Time stamps, geolocation, device information, identifying student information, time-on-page tracking, communications, details of interactions with librarians, library materials or equipment looked at, downloaded, or checked out, attendance at library classes or workshops, date and time of each entry into a swipe-carded library space, URLs and other information about websites visited.	Time stamps, geolocation, device information, and identifying student information.
Institutional goals		
Improved access to course and library materials as well as librarians and better tracking of material usage.	Unifying data from across library systems and monitoring resource and service use.	Study of student use or underuse of campus spaces, analyzing social connections based on students sharing similar campus space or attending campus events; enhancing campus safety by supporting campus security; supporting data-based decisions regarding campus investments.
Other units in the university may access collected data for goals not listed here.		
Rationale for data collection		
Increased student awareness of and seamless access to resources and expertise as well as informing library purchase decisions and assessing readings.	Potential to create or improve programs that help students academically, targeting students for outreach to connect them with additional resources, improved library operations, and possibly better integration into the university data warehouse.	Using campus space use information to make more informed decisions about campus budgets and to optimize the campus's spaces to support student success.



Trust questions (the “general question”)		
Do you trust the library to collect, use, or share the data in this scenario?	Do you trust the library to collect, use, or share the data in this scenario?	Do you trust the institution to collect, use, or share the data in this scenario?
Trust alterations		
1. Instead of being unidentifiable in the data, you are now directly identifiable. 2. Instead of the data being used solely for educational purposes, they are now used also for administrative purposes (e.g., financial, political). 3. Instead of the library being the main user of the data, the data are now widely used by university employees.	1. Instead of being identifiable in the data, you are now directly unidentifiable. 2. Instead of the data being used solely for educational purposes, they are now used also for administrative purposes (e.g., financial, political). 3. Instead of the library being the main user of the data, the data are now widely used by university employees.	1. Instead of being identifiable in the data, you are now directly unidentifiable. 2. Instead of the data being used solely for educational purposes, they are now used also for administrative purposes (e.g., financial, political). 3. Instead of the institution being the main user of the data, the data are now widely used by university employees.
Trust consensus		
Assuming that the sustainability of this technology requires this group’s consensus . . . what conditions might you all agree on to ensure your trust expectations are respected in the technology?		
Privacy questions (the “general question”)		
Do you think your privacy is or isn’t respected by the library in the scenario?	Do you think your privacy is or isn’t respected by the library in the scenario?	Do you think your privacy is or isn’t respected by the university / college or companies in the scenario?
Privacy alterations		
Instead of being unidentifiable in the data, you are now directly identifiable.	Instead of being identifiable in the data, you are now directly unidentifiable.	Instead of being identifiable in the data, you are now directly unidentifiable.
Privacy consensus		
Assuming that the sustainability of this technology requires this group’s consensus . . . what conditions might you all agree on to ensure your privacy expectations are respected in the technology?		

This manuscript is under review and accepted for publication, portal 23.3.



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This mss. is peer reviewed, copy edited, and accepted for publication, portal 23.3.