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Amplifying Student and Administrator Perspectives on Equity and Bias in Learning Analytics: Alone Together in Higher Education

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Abstract

When higher education institutions (HEIs) have the potential to collect large amounts of learner data, it is important to consider the spectrum of stakeholders involved with and impacted by the use of learning analytics. This qualitative research study aims to understand the degree of concern with issues of bias and equity in the uses of learner data as perceived by students, diversity and inclusion leaders, and senior administrative leaders in HEIs. An interview study was designed to investigate stakeholder voices that generate, collect, and utilize learning analytics from eight HEIs in the United States. A phased inductive coding analysis revealed similarities and differences in the three stakeholder groups regarding concerns about bias and equity in the uses of learner data. The study findings suggest that stakeholders have varying degrees of data literacy, thus creating conditions of inequality and bias in learning data. By centring the values of these critical stakeholder groups and acknowledging that intersections and hierarchies of power are critical to authentic inclusion, this study provides additional insight into proactive measures that institutions could take to improve equity, transparency, and accountability in their responsible learning analytics efforts.

Notes for Practice

- Centralize institutional decision-making around the adoption and implementation of data-collecting platforms in ways that are easily understandable across a range of data literacies to support equity.
- Generate pathways for continued stakeholder engagement, including student government and student group meetings, to involve stakeholders in data policy creation, process development, and reporting.
- Build organizational processes to facilitate collaboration with stakeholder groups focused on mitigating bias and supporting equity in the institutional collection and use of learner data.
- Engage faculty and administrative staff in professional development centred on equitable and inclusive practices as they relate to data policy and practice specifically.
- Audit and gather feedback on existing learner data policies on a regular basis to create a culture of continuous improvement.

Keywords

Stakeholder perspectives, bias, equity, learning analytics, higher education

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1. Introduction

While the teacher–learner relationship is of critical importance to all educational contexts, post-secondary students spend a significant portion of their time with staff and administrators, and the relationship among these groups is comparatively understudied (Luedke, 2017). Moreover, the studies that do exist often identify student expressions of distrust and concern about the extent to which their voices are considered by university decision-makers (Hon & Brunner, 2002; Luedke, 2017; Ropers-Huilman et al., 2005). To that end, this article draws on interviews with students, diversity and inclusion leaders, and senior administrative leaders in higher education institutions (HEIs) to examine their respective degrees of concern with issues of bias and equity in the use of learner data. In contrasting the responses of these different groups, we will consider the language each group uses to discuss their concerns, or lack thereof, and consider whether the relative positions along the institutional power spectrum of different stakeholder inform these responses. In doing so, we aim to shape the approaches institutional decision-makers and practitioners might take in developing a more responsible learning analytics system that centres on stakeholder voice.

As online education continues to grow and more on-campus students are taking online courses, there is an expansion of learner data (e.g., data from learning management systems [LMSs]) available for institutions to explore. The overarching questions are these: How is this data being used? and How much do students understand about the LMS data collected about them? The path towards a more "responsible" learning analytics (LA) practice requires a holistic approach to LA systems (Chen & Zhu, 2019) that "[pries] open the black boxes higher education institutions (and increasingly venture capital and learning management system providers) use to admit, steer, predict and prescribe students' learning journey" (Prinsloo, 2020, p. 4). "Black box" typically refers to opaque algorithmic systems and proprietary educational technologies inaccessible to their users (either incidentally or by design). Importantly, in this context, "black box" might also refer to the HEIs themselves, whose operations are often equally opaque to both internal and external observers (Brown, 2017). Thus, an essential step towards a more responsible LA is to illuminate the positionality and voices of various stakeholder groups embedded within these historically hegemonic structures so that the members of these groups might be given a clearer voice and treated not as reducible data but rather as whole persons.

As the field of LA matures, practitioners increasingly contend with issues regarding bias, privacy, ethics, and equity. At the root of these issues is the imperative to centre student perspectives, participation, and welfare. While explicit research and guidance on building trust with students as partners is scarce (Tsai et al., 2020), seminal work adopting value-sensitive design provides a structured approach to technical design processes that prioritizes human values (Friedman & Hendry, 2019). Researchers have demonstrated the promise of value-sensitive, human-centred design approaches in shaping holistic understandings of LA that subordinate process optimization goals to the well-being of the persons involved (Ahn et al., 2019; Chen & Zhu, 2019). Such processes typically begin by engaging the relevant stakeholder populations, which could include students, faculty, administrators, and a wide range of staff (Dollinger et al., 2019). These stakeholder groups are situated within a hierarchy of institutional influence over the form and function of LA, and differences in influence and perspectives among and within these groups are consequential to the adoption and use of learning data systems (Prinsloo, 2020). Inclusive participatory engagement with stakeholders, particularly those with limited institutional power, enables more human-centred design approaches to LA (Broughan & Prinsloo, 2020; Buckingham Shum et al., 2019) and addresses the gap in domain-specific contributions to the broader conversation around bias and equity in decision-making (Holstein & Doroudi, 2019).

2. Background

Essential questions around the ethical application of learning analytics in higher education have been established for some time now. Ethics and privacy concerns were featured in the planning conversations for the First International Conference on Learning Analytics & Knowledge, or LAK (Siemens, 2013). Additionally, Slade and Prinsloo (2013) suggested that learning analytics "is primarily a moral and educational practice" (p. 1526) in their systematic outline of the ethical challenges raised by LA practice in higher education. Additional researchers centred ethical questions in their LA research from this era (Ferguson, 2013; Rubel & Jones, 2016; Swenson, 2014), and others took substantive steps to frame their work in an ethical and responsible way (Ferguson & Buckingham Shum, 2012; Macfadyen & Dawson, 2012). For many, though, questions addressing the privacy and ethical implications of LA work were treated as afterthoughts, if at all, and the implementation of meaningful ethical frameworks to direct policy and practice has often lagged implementation efforts.

Notably, Viberg et al.'s (2018) seminal analysis of learning analytics research from 2012 to 2018 found that only 18% of studies even mention "ethics" or "privacy." Select practitioners were making substantive contributions toward ethical standards for the field, but the implementation of evidence-based guidelines in LA work was not yet widespread (Tzimas & Demetriadis, 2021). For instance, Drachsler & Greller's (2016) DELICATE framework provided a prominent example of a systematic framework for evaluating the ethical use of educational data in LA solutions, and a growing number of institutional codes of ethics were established around that time (Lang et al., 2018). Nonetheless, only a small number of institutions established policies before practice (Tsai & Gašević, 2017). As the LA discipline now reaches the end of what might be termed its beginning era (Conde & Hernández-García, 2019), several steps remain to be taken for a more mature application of LA to take root in higher education. Indicators that the LA field has emerged into a more mature practice that addresses the ethical challenges of this new era (Ferguson, 2019) would necessarily include the widespread adoption of practices that centre on privacy and transparency (Ferguson, 2019; Scheffel et al., 2019) and be marked by the equitable involvement of a range of stakeholders (Broughan & Prinsloo, 2020; Scheffel et al., 2019; Buckingham Shum et al., 2019) that attends more closely to context (Ferguson, 2019).

2.1. Stakeholder Voices

Calls from both the learning sciences and design fields have emerged to emphasize the importance of stakeholder voices. Philip, Bang, and Jackson's (2018) charge for the Cognition and Instruction community to rethink the "For What," "For Whom," and "With Whom" of their scholarship is indicative of many critical conversations taking place within the learning sciences. Contemporary LA work frequently draws on the practices of human-centred and value sensitive design to centre stakeholder perspectives (Ahn et al., 2019; Broughan & Prinsloo, 2020; Chen & Zhu, 2019; Dollinger et al., 2019; Buckingham Shum et al., 2019). Several researchers have taken steps to centre student voice specifically in LA practice (Broughan & Prinsloo, 2020; Ifenthaler & Schumacher, 2016; Jones et al., 2020; Li et al., 2022). Yet, more work remains to be done to better illuminate higher education stakeholder perspectives on fairness, equity, and responsibility.

For instance, the organizational structures and data imaginary of higher education are embedded with an inherent differential in power and authority between, and sometimes within, stakeholder groups (Prinsloo, 2020). Situated learning theory suggests that understanding power is essential to understanding learning (Esmonde, 2016). The scale and speed at which data science can drive action further accentuates the importance of this understanding (Green, 2021). Centring student voice, in itself, is not sufficient given students' situatedness within institutional processes marked by asymmetries in power (Prinsloo et al., 2018). Institutional efforts to engage stakeholders equitably in LA design and implementation require that practitioners within these spaces "directly attend to the intersections of macro-levels of power, micro-levels of individual cognition and cultural practice, and the meso-level contexts that link them" (Bethune et al., 2020, p. 469).

Acknowledging intersections and hierarchies of power are critical to the authentic inclusion of student voices in shaping institutional policy and practice, particularly regarding issues of bias and equity in the use of learner data. Explicit research on student perspectives of barriers to LA adoption is scarce, particularly around notions of trust (Tsai et al., 2020). Some have recognized the problematic framing of learners as data constructs removed from socio-historical contexts (Danaher et al., 2013; Perrotta & Williamson, 2018). Particularly within online education, the "crushing weightlessness of virtuality" (Doughty, 2014) increases the likelihood of exclusion or erasure of student perspectives. This is particularly concerning given the significant silence on issues of ethics in learning analytics research (Colvin et al., 2016) as well as the potential for disproportionate burdens and misallocated benefits within learning analytics systems (Rubel & Jones, 2016). While some learning analytics research recommends student involvement in decision-making as a core practice (Roberts et al., 2016), the inclusion of student voices within administrative decision-making requires more than "putting ourselves in the shoes of an opposing view" through proxy representation; instead, it necessitates an earnest engagement with objectionable beliefs and dissent (Funes & Mackness, 2018).

Increasingly, education literature has adopted critical discourse analysis as a lens through which to examine the ways the discourse of an educational institution enculturates values and paradigms across the organizational landscape, including administrative and technological norms (Gee & Handford, 2013; Rogers et al., 2016; Subotzky & Prinsloo, 2011). The social dynamics of institutional discourse, from the language participants use to the ways they can access and contribute safely to discursive spaces, is complicated by issues of power, identity, and positionality (Selwyn, 2015). Critical interrogation of normative discourse requires questioning assumptions about participant power and access to ongoing institutional conversations (Hope, 2015). In circumstances where the voices of stakeholders with little hierarchical power are marginalized, dominant narratives may entrench institutional norms that ignore their perspectives and lived experiences (Gourlay, 2015).

In this study, we begin by examining student perspectives on bias and equity in learner and learning data. While placing student voices in relation to any of the major stakeholder groups in higher education (i.e., faculty, data analysts, etc.) might contribute to the development of more responsible learning analytics, we aim to address a specific gap in the literature by comparing student and administrator perspectives (Hon & Brunner, 2002; Luedke, 2017; Ropers-Huilman et al., 2005); in this case, we specifically examine senior academic administrators and leading diversity and inclusion leaders. We draw on discourse analysis to highlight between-group and within-group contrasts and intersections related to acknowledgment, understanding, and urgency of issues of LA bias and equity, including how data is created, collected, and used for institutional purposes. Investigating relative homogeneity in perspectives through the lens of institutional power, we seek to address a gap in literature related to multiperspective, diverse, and interdisciplinary contributions to LA policy and praxis. A mature learning analytics is a responsible learning analytics; and a responsible learning analytics is one that acknowledges, and works to address, the inherent power discrepancy that exists between stakeholder groups engaged in learning analytics efforts at HEIs.

3. Methods

This research was part of a larger study conducted by a cohort of the Online Teaching and Learning Research Seminars program hosted by the Oregon State University Ecampus Research Unit. The group consisted of 10 cohort members, all of whom were employed by eight different HEIs in the United States during the time of data collection. Members of this group were selected from a pool of applicants based on their research experience as well as expertise related to learning analytics. These researchers each had multiple years of experience in online higher education and thus were positioned to consider the implications of learning analytics in online education.

The research team met in 2019 when they conceptualized the larger qualitative project, began the process of designing interview protocols, planned participant recruitment, and drafted an Institutional Review Board (IRB) application. During the following few weeks, the group worked to obtain approval from the IRBs of all required institutions. The research team worked to recruit participants and conduct virtual interviews during the following year. All of the data were collected during the onset of the COVID-19 pandemic (March–September 2020), and participant perspectives may have been impacted by that situation.

The larger study interview protocols included questions in the following areas: 1) definitions and general uses of data in higher education, 2) perceived benefits, helpfulness, and utility of learning and learner data, 3) perceived barriers, challenges, or concerns about learning and learner data, 4) perceptions of privacy, transparency, consent, and autonomy related to data in higher education, and 5) data uses and limitations. The current study is focused on an analysis of two of the interview questions:

1. To what degree are you concerned with issues of bias in the uses of learner data?
2. To what degree are you concerned with issues of equity in the uses of learner data?

3.1. Participant Sampling and Recruitment

Participants were from the institutions where the research team members were employed at the time of data collection. The recruitment processes for student participants differed from those for other stakeholder groups. Students were recruited from only three institutions chosen based on their location in different areas in the United States. The three research team members recruiting students obtained a random list of 100 student emails from their institutions that met recruitment criteria (see Table 1). Team members then sent recruitment emails. At each institution, if 10 students did not sign up for the study, then the research team member obtained another list of 100 students and sent recruitment emails to them. This process was repeated until 10 students were recruited from each institution. Students were sent up to two follow-up emails after the initial recruitment email.

For the administrators/diversity and inclusion leaders, team members at the eight institutions aimed to recruit two participants from each stakeholder group at their institution. Each team member generated email lists of individuals employed by their universities that fit recruitment criteria for each stakeholder group (see Table 1). Once the lists were generated, team members sent recruitment emails to each potential participant. The order in which they emailed potential participants on the list was randomized. Team members continued to send recruitment emails until they had recruited two participants in each stakeholder group. These individuals were sent up to two follow-up emails after the initial recruitment email.

Table 1. Recruitment Criteria for Stakeholder Groups in the Current Study

Stakeholder Group	Sample Titles	Description
Students	Undergraduate student, graduate student, on-campus student, online student, degree-seeking student	Undergraduate or graduate, on-campus or online, degree-seeking with more than one year (2 semesters or 3 quarters, not including summer terms) of experience at the institution.
Diversity and Inclusion Leaders	Director of equal opportunity and affirmative action, director of disability services, director of gender equity centre, director of cultural centres	Roles which, as a primary responsibility, lead and/or direct diversity, equity, and inclusion (DEI) efforts across campus, particularly in the supervision of campus units or entities that facilitate programming and support for students of marginalized and/or underserved identities.
Administrators	Assistant/associate vice president (VP) of academic affairs, assistant/associate VP of student affairs, assistant/associate VP of undergraduate studies, assistant/associate VP of educational initiatives	Staff who work in a centrally located administrative position (i.e., not located within a school/department) who are primarily responsible for leadership and/or oversight around teaching and learning initiatives or endeavours.

Note. All stakeholder groups were recruited from HEIs in the United States.

For all stakeholder groups, recruitment emails contained a link to an anonymous Qualtrics pre-survey that asked participants for their demographic information, as well as contact information. Each participant was assigned to one of the ten team member interviewers who emailed them to schedule a 60-minute interview via Zoom. Participants who failed to respond to email invitations to schedule an interview were removed from the participant pool, and new individuals from their institutions were recruited in their place.

3.2. Interviews

Interviewers used a structured interview approach where they read interview questions from the protocol with few or no follow-up questions. Interviews were recorded and transcribed for data analysis. Upon completion of the interview, participants were compensated with a $25 e-gift card.

3.2.1. Sample Characteristics

For this study, we analyzed the interviews with the following stakeholders: 20 students, five diversity and inclusion leaders and five administrators.

3.2.2. Students

While most of the participants in the stakeholder groups completed the pre-survey and interviews, more than twice the number of students completed the pre-survey (N = 46) than completed the interview (N = 20). To maintain anonymity, we did not collect identifying information in the pre-survey and thus were unable to connect pre-survey data to the interviewees. The descriptive statistics for the 46 students are provided here, however, over half of these respondents were not interviewed. Of the 46 students who completed the pre-survey, 17 (37%) identified as 18–30 years, and 29 (63%) identified as 31 years and older. An equal number of students identified as male (n = 23) and female (n = 23). While the majority (63%) of the sample identified as White (n = 29), other groups were represented, including Black or African American (n = 8, 17%), Hispanic (n = 3, 6.5%), and Asian (n = 3, 6.5%) students. More than half of the students were enrolled in all online courses (n = 25, 54%), with most of the rest enrolled in a combination of online and face-to-face courses (n = 17, 37%). Roughly half (n = 25, 54%) of these students were enrolled full-time, with a substantial proportion enrolled part-time (n = 17, 37%). Some were not sure if they were part-time of full-time students (n = 4, 9%). A small proportion (n = 7, 15%) reported being first-generation college students, and students represented diverse majors and fields of study. These demographic statistics suggest that the sample more closely resembled an online learner population. The student interviews ranged from 20 to 101 minutes with a mean length of 51 minutes (SD=19).

Table 2. Pre-Survey Demographics of Participants

	Students (N=46)	Diversity and Inclusion Leaders (N=4)	Administrators (N=5)
	f (%)	f (%)	f (%)
Age			
18–30	17 (37%)	—	—
31 years and older	29 (63%)	4 (100%)	5 (100%)
Gender			
Female	23 (50%)	1 (25%)	4 (80%)
Male	23 (50%)	1 (25%)	1 (20%)
Gender queer/non-conforming/fluid		2 (50%)	
Race/Ethnicity			
American Indian/Native	2 (4.3%)	—	—
Asian	3 (6.5%)	1 (25%)	—
Black or African American	8 (17.4%)	2 (50%)	1 (20%)
Hispanic	3 (6.5%)	—	—
Other	1 (2.2%)	—	—
White	29 (63%)	1 (25%)	4 (80%)

3.2.3. Diversity and Inclusion Leaders

Four of the five diversity and inclusion leaders who completed the interview completed the pre-survey. Of the four, one identified as male, one female, and two gender queer/non-conforming/fluid. They ranged in age from 36 to 60 years old and had worked as diversity and inclusion leaders for 1.5 to 9 years (M = 4.1 years). They identified as Black or African American (n = 2), White (n = 1), and Asian (n = 1). Three reported working at public universities, while one worked at a private university. The diversity and inclusion leadership interviews ranged from 39 to 84 minutes with a mean length of 57 minutes (SD=17).

3.2.4. Administrators
All five of the administrators who completed the interview completed the pre-survey. Four identified as male and one female. They ranged in age from 36 to over 60 years old and had worked as administrators for 5 to 20 years (M = 8.5 years). Most identified as White (n = 4), with one who identified as Black or African American. Three reported working at public universities while two worked at private universities. The administrator interviews ranged from 56 to 122 minutes with a mean length of 72 minutes (SD=28).

3.3. Qualitative Data Analysis
The four authors of this study began with the student responses to the interview questions. We completed a round of pre-coding where we read through all participant responses and identified categories and themes. The authors discussed potential coding strategies and decided to use an inductive approach with structural coding (Saldaña, 2021) to categorize data across multiple participant groups to address the research questions.

The authors reviewed the student responses again and began generating a codebook (see Table 3). The student codebook includes a code name, description, inclusion/exclusion criteria, and example data types for each code. All coding was completed using text colours, highlights, and comments in Microsoft Excel.

Table 3. Codebook for Student Responses

Code	Description	Inclusion/Exclusion Criteria	Examples
Degree of concern	Participant describes their thoughts and feelings related to their level of concern about learning data. Sub code: None/low; I don't know, High	**Includes**: No/low level of concern or specific types of concerns, worries, or conflicting levels of concern, about learner data; those who talked about learner data. **Excludes**: Those who talked about research data.	"The only concern I guess I would have with that sort of issue is… I think data by itself is good, but I think it's when people come into play is when it can be used bad or with dishonest reasoning."
Relationship with stakeholders	Participant identifies people and stakeholders or relationships with people who are responsible for collecting and analyzing learning data.	**Includes**: Professors, deans, instructors, faculty, peers, review board, students, administrative offices and processes, and institutional representatives; only includes those who talked about learner data. **Excludes**: Those who talked about research data.	"Because I don't know who's behind the curtain. I don't know how it's being interpreted. I don't know what experiences people have, where they're coming from for them to interpret anything, especially if it has anything to do with me."
Biased decisions in learner data analysis	Participant identifies learner data being used to make decisions about the educational process and describes these decisions as being influenced or biased.	**Includes**: Course level learning activities, grades, course evaluations, exams, admission, program progress, and finals; mention of demographics broadly. **Excludes**: Mention of specific identity markers.	"So, there are other, like the intangibles and other environmental factors that impact the data, and if those aren't considered in making decisions, it can be problematic. If they are considered, it can actually be helpful because it can strengthen the data."
Specific identity markers	Participant shares a reference to an identity marker in relationship to bias in the collection or use of learner data.	**Includes**: Minority, race, stereotype, demographic, location, gender, geography, age, ability, first generation, program of study, learning preference, learning characteristics, socioeconomic status, sexuality, nationality. **Excludes**: Mention of demographics broadly.	"So, I don't see it. I've never heard much… I know there's stereotypes and things like that, but as far as my particular demographic, I don't feel that there's a concern for me, because it's always been positive."

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Limitations of learner data	Participant provides examples or demonstrates awareness of the limitations of or access to learner data.	**Includes**: Data incomplete, data inaccurate, wrong focus on data, non-reflective interpretations, lack of context for interpretation, unequal representation in data, grades as a diagnostic of learning, predictive analytics; only include those who talked about learner data. **Excludes**: Faculty, course evaluation data.	"I think that's where there's a danger in data because yeah, you look at it and you don't get to see that person, or what are the other mitigating factors? I think that data doesn't sometimes motivate people to ask additional questions."
Non-learner data	Participant discusses data that are not related to their own educational activities and performance.	**Includes:** Research data, data for course work, faculty evaluations.	"If I'm just doing some preliminary research for whatever project, sure if I can start out with a number of resources and they may not all necessarily be true, considerably reliable, but just to get the start."

After completing the coding for students, the authors completed a round of pre-coding the responses of diversity and inclusion leaders/administrators to the two research questions. The authors discussed how the codes generated from the analysis of student responses were similar and what codes would be retained. They also discussed which codes needed to be modified to capture the responses of the administrators/diversity and inclusion leaders. The resulting administrator/diversity inclusion leader codebook is shown in Table 4. A direct comparison of the codes for the two analysis groups is shown in Table 5. All responses collected were negotiated to meet an inter-rater reliability of 100% to interpret meaning from the data.

Table 4. Codebook for Responses of Diversity and Inclusion Leaders/Administrators

Code	Description	Inclusion/Exclusion Criteria	Examples
Degree of concern	Participant describes their thoughts and feelings related to their level of concern about learning data. Sub code: None/low; I don't know, High.	**Includes**: No/low level of concern or specific types of concerns, worries, or conflicting levels of concern about learner data.	"I am very concerned about the bias that surrounds user data, what we do with it, how we analyze it, who's doing the analysis."
Concerns about data processes	Participant identifies concerns or problems with processes that include collecting data, interpreting data, access to data and regulations related to data.	**Includes**: Algorithms, human intervention, automation, tracking, monitoring, evaluating, how the data is gathered, analysis of data, reporting and transparency of communication, who is collecting the data and how it's being processed, the frequency and the number of people involved in the process, policy, compliance, and safeguards.	"I think I have an amount of concern that whatever you put into the black box algorithm, someone's made a decision as to what goes in there, and someone's made a decision as to how it is measured."
Biased decision-making	Participant identifies learner data being used to make decisions about the educational process and describes these decisions being influenced or biased.	**Includes**: Demographic data, references to proxy and dimensions of data, references to good and bad data or other binary references such as Black and White.	"Because sometimes, if we analyze data through our lens, so if I analyze data as a Black male who had an urban upbringing, I'm looking at those data, and I need to acknowledge that. And how I'm interpreting the data."

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Limitations of data for usefulness	Participant shares a reference to or a perception of limitations of data used to inform the student learning experience; may suggest a question of doubt.	**Includes**: A reference to trust, reliability, validity, generalizability, objective vs. subjective, skepticism.	"Understanding that students of colour may have different learning needs than their White peers. Transgender students have a fundamentally different experience in the classroom than their peers."
Reducing the bias (ways to mitigate bias)	Participant provides examples of ways to reduce bias or expresses a need to address or mitigate bias.	**Includes**: Suggests solutions through faculty/professional development, literacy and training to develop skills and competencies, more people involved in the process will reduce bias through diverse lenses, benchmarking bias, right intentions and heart, training.	"But I think because we have a lot of eyes on it, because we have other, more than one means to measure some of those learning outcomes that it's kind of almost like a check and I think it helps."

Table 5. Comparison of Codes: Student vs. Diversity and Inclusion Leaders/Administrators

Students	Diversity and Inclusion Leaders/Administrators
Degree of concern	Degree of concern
Biased decisions in learner data analysis	Biased decision-making
Limitations of learner data	Limitations of data for usefulness
Relationship with stakeholders	Concerns about data processes
Specific identity markers	Reducing the bias (ways to mitigate bias)
Non-learner data	

4. Results and Discussion

This research aims to understand the degree of concern with issues of bias and equity in the uses of learner data as perceived by students, diversity and inclusion leaders, and administrative leadership in HEIs. The analysis of student data resulted in five categorical dimensions of concern that include the degree of concern, biased decisions in learner data analysis, limitations of learner data, relationships with stakeholders, and specific identity markers. An additional category of references to bias and equity in non-learner data was also used (see Table 4). Accordingly, researchers employed five categorical dimensions of bias and equity, informed by the student data analysis, to shape the analysis lens of data collected from administrators/diversity and inclusion leaders (Table 4). As a result, a total of 139 references were coded and are presented in Table 6. The tables show the number of times the codes were identified in the interviews. Thus, individual participants may be included more than once in these frequencies.

The following section will begin by examining common themes that emerged from the three stakeholder voices, then proceed to the nuanced themes by stakeholder group.

4.1. Shared Voices

Our first finding categorizes the top three themes that converged across all stakeholder groups. The most frequent themes expressed by students, diversity and inclusion leaders, and university administrators were degrees of concern with bias and equity in learning analytics, biased decision-making, and limitations of learning data.

4.1.1. Degrees of Concern with Bias and Equity

First, stakeholders shared a significant concern about bias and equity in learning data. From the student perspective, participants shared a degree of concern about bias, ranging from not concerned to very concerned. The spectrum of student concern included responses such as "In the online form, not much a concern. I haven't seen it," to moderate levels of concern such as "Basically, I am somewhat concerned about people using their bias and the bias in data," to higher levels of concern including, "Well, that's a big concern, considering I'm a minority." Conversely, when asked the same question, a diversity and inclusion leader responded that bias "is a concern of mine. And I do know that sometimes, I've even heard it when people can look at a name and say, you know, they'll notice this is a minority or whatever. That bothers me." This theme continues with administrative leaders and other diversity and inclusion leaders who expressed substantial degrees of concern with bias in learning data. In a similar response, two administrative leaders indicated that bias will always be a concern, with one who shared, "Bias is always going to be there. I think my greater concern is that we're not acknowledging it."

Table 6. Participant Concerns of Bias and Equity in Learning Data

Student Code Reference	Reference Frequency
Degree of concern — Bias	18
Degree of concern — Equity	16
Biased decisions in the analysis of learning data — Bias	10
Biased decisions in the analysis of learning data — Equity	9
Limitations of learner data — Equity	6
Limitations of learner data — Bias	5
Relationship with stakeholders — Equity	5
Specific identity markers — Bias	5
Relationship with stakeholders — Bias	4
Specific identity markers — Equity	3
Non-learner data — Equity	3
Non-learner data — Bias	2
Administrator and Diversity & Inclusion Leaders Code Reference	**Reference Frequency**
Degree of concern — Bias	7
Concerns about data processes — Bias	7
Limitations of data for usefulness — Bias	7
Concerns about data processes — Equity	6
Biased decision-making — Bias	5
Biased decision-making — Equity	5
Degree of concern — Equity	5
Reducing the bias — Bias	5
Reducing the bias — Equity	4
Limitations of data for usefulness — Equity	2

The degree of concern regarding equity in learning analytics was frequently discussed among stakeholders. In particular, students were unable to address the question because they appeared to not fully understand the interview questions. In comparison, diversity and inclusion leaders/administrators expressed a significant degree of concern with equity in the extraction, protection, and decision-making processes. These university employees, administrators/diversity and inclusion leaders acknowledged that equity is "a valid concern and it's real" and "I think any institution has to be concerned … and maybe an institution like ours even more so, because we can extract so much data from our online learning classrooms." The polarized degrees of concern in the responses from student stakeholders and university personnel illustrate the systemic ethical challenges and opportunities that plague the use of data in educational practice. This first theme aligns with previous research conducted by scholars Slade and Prinsloo (2013) and Tsai et al. (2020) in which the lack of acknowledgment across all stakeholder groups to enable student agency, value student identity, provide transparency on the use of learning data, and leverage the student perspective to inform practice and learning continues to be amiss in the conversation of equity in learning analytics.

4.1.2. Biased Decision-Making

The second theme regarding bias and equity in learning data is biased decision-making. More than half of the student stakeholders expressed their awareness that learner data might be used to justify decisions that could be influenced or biased. For example, a student participant suggested, "I think people could use the data and show it in a certain way to hurt other people." Further, other student stakeholders made specific references to the interpretation of data and that those who conduct

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the analysis have "preconceived notions" that obstruct the results. For example, one student shared the following:

> I think that it depends how you're analyzing the data and how you are… Sometimes in the people analyzing it, they can have some sort of preconceived notion, and it's important to know that the people who are actually analyzing the data, that they will have a neutral and a real focus on the data itself, and not on the notions of the preconceived information that they had.

Administrators also emphasized the role of analysis and interpretation of learner data. In unison with the student stakeholders, one administrator discussed the influence of personal biases of the individuals interpreting the data. They stated, "[t]he data may help them prove their biases." Another administrator also talked about the interpretation of data from complicated algorithms and shared, "people may take that as, well, it looks complicated; therefore, it must be true." Of the three groups, diversity and inclusion leaders made the fewest references to biased decision-making. Instead, they took a reflective approach and shifted the conversation inward to their own experiences and capabilities. For example, a diversity and inclusion leader expressed their own "struggle" with personal biases and acknowledged that their own bias might lead to assumptions about students. Another diversity and inclusion leader questioned, "how could you even prove that someone was holding information back based on a bias they had of a student?" This theme establishes the relationship between bias and equity in stakeholder perspectives of learning analytics. Bias emerges as the predecessor in which those who interpret and analyze learner data act as judge and jury to enable or disable equity in learning.

4.1.3. Limitations of Learning Data

The third concern across stakeholder groups involves the limitations of learner data (student population) and the limitations of the usefulness of that data (administrators/diversity and inclusion leaders). The original theme was based on student awareness of the limitations of or access to learner data. Informed by the first phase of analysis, this code was modified for administrator/diversity and inclusion leader participants as limitations of data or perception of limitations of data used to inform the student learning experience. All stakeholder groups suggested a level of doubt or skepticism about learning data. They suggested a disconnect between how data is generated, collected, and interpreted. One student questioned "the reliability of the source" and completed their thought with "there could be available data that's skewed whichever way." Another student stated, "Data says a lot of things about you, but they don't know you," this skepticism was elaborated further by a diversity and inclusion leader who said this:

> I'm really concerned that the ways in which we collect data now don't take into account different learning preferences, different learning needs, and the different backgrounds of our students. Understanding that students of colour may have different learning needs than their white peers. Transgender students have a fundamentally different experience in the classroom than their peers.

The disconnect is further summarized by an administrator who reported, "sometimes we're not very clear on how data were collected. We'll just get a report put in front of us."

4.2. Alone Together

Our second section of findings includes four themes where stakeholder groups diverged on their degree of concern about bias and equity in learning analytics. Additionally, a central finding is that students demonstrated low levels of awareness and literacy regarding learning data and analytics overall. In many cases, student responses suggested that they had limited knowledge or understanding of the learning data collected about them.

The first two themes presented arose from the student perspective and include relationships with stakeholders and specific identity markers. The remaining two themes were identified from the administrator/diversity and inclusion leader perspective, including concerns about data processes and potential solutions to reduce bias.

4.2.1. Relationships with Stakeholders

The first student theme that differed from the other two groups was relationships with stakeholders. The students interviewed specifically identify stakeholders or relationships with people responsible for collecting and analyzing learning data. These participant responses reflect an acknowledgment that professors, admissions staff, and department heads were in positions of power and control and that bias may enter how data is interpreted. In an example, a student shared the following:

> I feel like a lot of the biases are coming from the upper levels. Something that I wouldn't even think to have any sort of control over. It's either the people that are actually in charge of the university admissions department, which I'm not even thinking about, then at the class level, the bias presence is given by the professors.

Student participants expressed skepticism in relationships with stakeholders and acknowledged their vulnerability to influence data-informed decision-making. One of them put it this way: "Because I don't know who's behind the curtain. I don't know how it's being interpreted. I don't know what experiences people have, where they're coming from for them to interpret anything, especially if it has anything to do with me."

At the same time, students recognized grades as data but could not speak to other data streams and analyses that may provide more equitable and personalized solutions. Student participants questioned the capability and current data practices of university stakeholders:

> So, in order to provide equity, you have to provide different supports. But I think just looking at specific data, like grades, doesn't tell you what you need to support every student. So, I think you have to look at a lot more, and I don't know if a lot of professors do that or [our university] does that. I couldn't tell you if they do or not, but I think that you do have to look a lot deeper into student work and thinking and not just their test scores and grades that are weighted a lot in a lot of our classes.

This theme presents the inequalities and power differentials between stakeholder groups in HEIs from the student perspective. From this view, students feel they have little influence regarding their learning data among faculty and administrative staff at their institutions. They expressed concern regarding bias and the equitable interpretation of their data.

4.2.2. Specific Identity Markers

In the second divergent theme among stakeholder groups, student participants referred to an identity marker concerning bias and equity in collecting or using learner data. Five student participants disclosed a reference to an identity marker, with four reporting a degree of concern because they identified as a minority. Of these students, comments were made about how "data is about the differences in people" and expressing familiarity with collecting demographic information, such as "usually when you fill out something, they ask you for your ethnicity, your gender, your age."

Students suggested that demographic categories created inequalities and could lead to stereotyping "like minorities tend not to do well in this, or women or people who are from this or whatever. They tend not to do well." Whereas one student felt their demographic was to their advantage: "for my particular demographic, it's always positive … I know there's stereotypes and things like that, but as far as my particular demographic, I don't feel that there's a concern for me, because it's always been positive." Another student indicated that demographic data could initiate bias: "I think that a lot of bias happens when talking about student demographics. I think that that's a really big one… I think there's a lot of stereotypes and bias that come out just based on where you're from and just what you identify with."

This theme addresses personal responses and reflections from the student perspective, indicating a transparent gap. The gap implies that students know that their demographic information is collected and gathered. However, again, students could not articulate or identify how HEIs analyze and apply demographic data to their processes and decision-making. In contrast, our next theme from the diversity and inclusion leader/administrator perspective does include concerns about data processes.

4.2.3. Concerns About Data Processes

The third theme that emerged from the administrators/diversity and inclusion leaders deals with concerns or problems with learning data processes such as collecting, interpreting, accessing data, and regulations related to data. This was a popular theme, as seven out of ten participants expressed concern about bias and six identified equity issues in learning data processes. Administrators/diversity and inclusion leaders questioned and pointed out that those who analyze, create models, and interpret data can inject inherent biases and create inequalities. As one administrator succinctly shared, "It's up to the person who is using the data." In contrast, another administrator expressed concern regarding the creation of automated processes and statistical models: "whatever you put into the black box algorithm, someone's made a decision as to what goes in there, and someone's made a decision as to how it is measured." Further, in a more critical reflection, a diversity and inclusion leader implied a disconnect between those who develop and conduct the analysis with those who receive and consume the finalized information stating,

> I am very concerned about the bias that surrounds user data, what we do with it, how we analyze it, who's doing the analysis. What were the questions asked to develop the data points that we gathered in the first place? Who developed those questions? And then once we get those data points back, who's doing the analysis? What is their mind like? What are their implicit biases? Shoot. What's their heart like? And then we'll get into other things. The people that provided you the data to establish the data points, where are they at? What were their implicit biases or not even implicit, just their biases towards the person who they're establishing the data on? There's always problems with data.

In addition, administrators/diversity and inclusion leaders shared concerns about data collection. As one of the administrators put it, "I think all data, we have to be concerned about really what's going in, how it was gathered." On a similar chord, a diversity and inclusion leader advocated "that effective data collection is designed with the deep understanding of the experiences of, perspectives of, and needs of broad groups of learners," and demographic data could inform the unique needs of students. This point shifts the student concern with specific identity markers by suggesting that demographic data could be used for the greater good to inform universal support systems and create more equitable learning experiences for all. However, this theme also makes more apparent the considerable disconnect among stakeholder perspectives. From the student's perspective, they lack knowledge of how the data collected about them impacts them. At the other end of the spectrum, administrators/diversity and inclusion leaders receive data analysis outputs but express concern and skepticism about the data interpretation because they have little impact on the methodology of data collection and analysis. One diversity and inclusion leader shared the importance of developing systems that take "into account and allow us to understand and use data as a tool for understanding bias rather than using data as a means to say, wow, students of colour aren't performing as well. Or, wow, our LGBTQ students just really can't hack it here." Similarly, an administrator stated that "data can really help us understand some of the factors that might be contributing to equity gaps or gaps in various variables." Thereby seeing learning data as a tool or solution to reduce inequalities in policies and processes hosted at the institution.

4.2.4. Reducing Bias

Finally, a fourth theme emerged from administrators/diversity and inclusion leaders who provided examples of ways to reduce bias or expressed potential solutions to address or mitigate bias. Some expressed a belief that involving more people in the data collection and analysis process would somehow reduce their concerns with bias and equity in their decision-making. For example, one administrator suggested that one safeguard for analyzing learning data "just needs to have a lot of people's eyes on it and not just one person's interpretation."

Pragmatically, many administrators/diversity and inclusion leaders cited potential solutions to reduce their concerns about bias and equity in learner data by improving their data collection, analysis, and interpretation literacy. Again, they called for more training and development to increase data literacy among university staff but did not include student stakeholders as part of these programs. A diversity and inclusion leader shared this: "I think a lot of it has to do with just being educated and knowing, you know, what's not appropriate. So, I do think it's a personnel training thing." Another administrator placed emphasis on training "people about data. That's why it is important to have policies and processes. How we are pulling data, who are we sharing it with? When we are sharing, are we providing them the resources they need to know to use the data effectively and factually?"

Unfortunately, most administrative/diversity and inclusion leader respondents did not express that engaging with a broad range of stakeholders, including students, to develop policy and practice could improve transparency and trust. For example, of all university-employed respondents in this study, only one diversity and inclusion leader recognized that "You took something from someone. How then are you giving them back that information? How are you using that to empower them to understand things? And so I think that's connected to equity, and social justice, and issues of discrimination…"

5. Conclusion

The research findings demonstrate a necessity to engage with stakeholders across the organizational hierarchy as part of decision-making about the use of learner data. While stakeholder groups — particularly students — are not homogenous, clear divergences in perspective about bias and equity arose that reflected institutional positionality. Notably, groups with lower institutional influence (in this case, students) exhibited comparatively limited awareness of how HEIs gather and use learner data; however, students did express concerns with data use related to identity, fairness, and trust in their relationships with staff and faculty. Conversely, staff and administrators articulated greater familiarity with learner data and weighed benefits of using it against risk and harms; however, few expressed notions of engaging students as partners in shared data governance. All stakeholder groups shared concerns about bias and inequity in decision-making as well as limitations of data to accurately represent learner experiences. These shared sentiments reveal practices that could, if affirmed through organizational priority and implementation, elevate student voices, remediate fragmentation among stakeholders, and increase trust between learners and members of the educational ecosystem that collect, interpret, and act on their data.

5.1. Implications for Practice

Based on the themes that emerged in this study, we have defined more equitable practices to reduce concerns of bias and inequality in learner data. At an institutional level, higher education leaders should shift institutional decision-making around the adoption and implementation of data-collecting platforms in approaches that are accessible and inclusive to all stakeholders. Consistent with the literature, the lack of digital and data literacy among institutional stakeholders remains a common barrier

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to effective implementation and equitable practice (Raffaghelli et al., 2020; Tsai & Gašević, 2017). Therefore, institutions need to encourage further discussion about digital and data literacy to ensure that all stakeholders, including students, can make informed decisions about the collection and interpretation of their data (Wasson et al., 2016). In addition, institutions should provide professional learning opportunities centred on cultural competency and inclusive leadership as they relate to data policy and practice specifically (Raffaghelli, 2020).

Institutions should build organizational processes to facilitate collaboration and feedback sessions with stakeholder groups focused on the institutional collection and use of student data. These internal processes and informational sessions must offer space where participants feel safe presenting ideas and concerns that may challenge dominant perspectives. Since learner data is multidimensional and complex — as demonstrated in the perspectives brought by the participants in this study and consistent with the literature (Prinsloo et al., 2018) — institutions should plan for disagreement among and within-participant groups around institutional policies and uses for learner data and engage in good-faith consensus-building efforts while documenting areas of dissent. Further, by taking a proactive approach, institutions can build transparency and improve digital and data literacy by incorporating stakeholder perspectives on the negotiation and acquisition of new digital platforms, including contract renewals and partnerships with third-party vendors. Additionally, institutions should develop pathways for continued stakeholder engagement, including student government or student group meetings, to encourage diverse stakeholder representation in data policy creation, process development, and reporting.

Finally, in order to provide a culture of continuous improvement, institutions should develop ongoing feedback loops on existing learner data policies and practices. At a minimum, institutions should create organizational processes for addressing anonymous, individual, or group reporting of experiences, or concerns around bias and equity.

5.2. Study Limitations

This study launched and began participant recruitment in March 2020, just as the global pandemic began to take shape in North America. Unfortunately, the pandemic created unforeseen challenges and barriers to recruiting potential participants and collecting data. Consequently, the conclusions that we can draw from this study are limited due to the low response rate, especially with the administrator/diversity and inclusion leader participant groups.

Additionally, as with most of the literature regarding learning analytics (Fynn et al., 2022; Prinsloo, 2018), this study demonstrates the voices of those from the Global North and neglects to amplify voices from the Global South. Therefore, we encourage future studies to build on this research with perspectives across socio-cultural, political, and economic contexts to guide the implementation and practice of equitable learning analytics.

Declaration of Conflicting Interest

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