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Fairness, Trust, Transparency, Equity, and Responsibility in Learning Analytics

Mohammad Khalil[1], Paul Prinsloo[2], Sharon Slade[3]

Abstract

Learning analytics has the capacity to provide potential benefit to a wide range of stakeholders within a range of educational contexts. It can provide prompt support to students, facilitate effective teaching, highlight aspects of course content that might be adapted, and predict a range of possible outcomes, such as students registering for more appropriate courses, supporting students' self-efficacy, or redesigning a course's pedagogical strategy. It will do all these things based on the assumptions and rules that learning analytics developers set out. As such, learning analytics can exacerbate existing inequalities such as unequal access to support or opportunities based on (any combination of) race, gender, culture, age, socioeconomic status, etc., or work to overcome the impact of such inequalities on realizing student potential. In this editorial, we introduce several selected articles that explore the principles of fairness, equity, and responsibility in the context of learning analytics. We discuss existing research and summarize the papers within this special section to outline what is known, and what remains to be explored. This editorial concludes by celebrating the breadth of work set out here, but also by suggesting that there are no simple answers to ensuring fairness, trust, transparency, equity, and responsibility in learning analytics. More needs to be done to ensure that our mutual understanding of responsible learning analytics continues to be embedded in the learning analytics research and design practice.

Notes for Practice

- This special section highlights trust, transparency, fairness, and responsibility as actionable ethics research areas in learning analytics.
- This special section features nine articles that offer critical perspectives on responsible learning analytics and highlight key emerging research in the field. The role of stakeholders in ensuring fairness and transparency, the importance of accountability in promoting trust, and the potential for data-driven systems to perpetuate existing inequalities has been widely covered in the selected papers.
- Questions around whether data-driven learning analytics support systems might advantage some students over others are raised, and responsible learning analytics are scoped in terms of education's moral obligation to ensure legal and ethical processes for the collection, analysis, and reporting of student data.
- Practitioners, researchers, and policy makers should be aware of the power dynamics inherent in learning analytics and should pay closer attention to designing learning that provides equitable experiences for marginalized students.

Keywords
Trust, transparency, fairness, equity, ethics, responsible learning analytics

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Corresponding author [1]Email: mohammad.khalil@uib.no Address: Centre for the Science of Learning & Technology (SLATE), University of Bergen, 5010 Bergen, Norway. ORCID ID: https://orcid.org/0000-0002-6860-4404
[2]Email: prinsp@unisa.ac.za Address: University of South Africa, Unisa, P.O. Box 392, Pretoria, 0003, South Africa. ORCID ID: https://orcid.org/0000-0002-1838-540X
[3]Email: sharon.slade@outlook.com Address: Earth Trust, Little Wittenham, Abingdon, OX14 4QZ, UK. ORCID ID: https://orcid.org/0000-0003-0130-8456

1. Introduction

Learning analytics is an interdisciplinary research field, founded in the broader context of data science and influenced by several theoretical perspectives and technological advancements such as artificial intelligence (AI), increased data processing capabilities, and greater volumes, variety, and velocity of data (Hernández-de-Menéndez et al., 2022; Zhu et al., 2022). It provides opportunities for data-driven insight aiming to support teachers and learners, and to optimize pedagogy and learning environments. Learning analytics increasingly relies on supervised and unsupervised algorithmic decision-making that may add to concerns around security (Khalil & Ebner, 2016), as well as equity, responsibility, and fairness (Prinsloo et al., 2023). Such concerns might also be considered for learning analytics as a whole (Holstein & Doroudi, 2019). A critical interrogation of "fairness," "equity," and "responsibility" in the context of learning analytics is therefore timely (Ferguson et al., 2022).

1.1. Background to the Special Section

Fairness, equity, and responsibility have been integral to discourses inside and outside of the learning analytics community since its emergence. Applications include ethical and privacy issues in learning analytics (Slade & Prinsloo, 2013; Khalil et al., 2018); responsible learning analytics (Prinsloo & Slade, 2018); human-centred learning analytics (Buckingham Shum et al., 2019), student-centred learning analytics (Broughan & Prinsloo, 2020); value-sensitive design (Chen & Zhu, 2019); the ethics of care (Prinsloo & Slade, 2017); social justice (Wise et al., 2021); student rights (Berendt et al., 2020); perspectives from data feminism (Garcia et al., 2020); critical data studies (Kitchin & Lauriault, 2014); and other related fields. Francis et al. (2020) and Baker and Hawn (2022) raise fairness and equity questions around whether data-driven learning analytics support systems might advantage some students over others. Cerratto Pargman and McGrath (2021) suggest that responsible learning analytics should be scoped in terms of legal, ethical, and effective processes for the collection, analysis, and reporting of student data.

This special section brings together diverse and critical perspectives, as well as approaches pertaining to fairness, equity, and responsibility, to highlight current and emerging conceptual and empirical research that will inform the broader research agenda in learning analytics. The issue includes nine articles covering a broad range of topics on responsible learning analytics.

1.2. Key Concepts and Questions

Each of the concepts at the centre of this special section — trust, transparency, fairness, equity, responsibility — is worthy of consideration in the context of learning analytics. How do these concepts also relate and contribute to *responsible* learning analytics? Prinsloo and Slade (2018) suggest that responsible learning analytics entails much more than institutions being accountable; institutions should also be response-*able* across the whole spectrum of educational delivery including planning, designing, implementing, and assuring quality in online learning. As such, responsible learning analytics — and the elements of trust, transparency, fairness, equity, and responsibility — must consider who benefits and on what basis. Responsible learning analytics is therefore, in its essence, relational and critical (Prinsloo & Slade, 2018) and arises from the fiduciary duty of institutions to make resources available and to act on actionable intelligence. In the context of responsible learning analytics, the obligation to act may be the elephant in the room (Prinsloo & Slade, 2017).

Also interesting (and possibly even more challenging) is to reflect on and critically engage with the theoretical and practical implications of considering all these concepts at the same time, whether in learning analytics design, in the shorter- or longer-term impacts of implementation, or in the development of policy.

The call for papers for this issue invited authors to consider a range of perspectives, including the following:

- Learning analytics, AI and equity, fairness, and responsibility: Issues of design, transparency, accountability, and governance (e.g., Grimm et al., 2023a; Holstein & Doroudi, 2019; Prinsloo et al., 2019).
- The design, implementation, risks, and benefits of learning analytics for minority and disadvantaged groups, such as students with disabilities, subcategories of unexplored demographics, migrants, etc. (e.g., Prinsloo et al., 2023; Skinner-Thompson, 2021).
- Theoretical perspectives on fairness, equity, and responsibility in learning analytics, such as from data feminism, intersectionality, critical data studies, and others (e.g., Buckingham Shum, 2019; Uttamchandani & Quick, 2022).
- Case studies of institutionalized approaches to improve/ensure fairness, equity, and responsibility in learning analytics (e.g., Jones et al., 2020; Ochoa et al., 2020).
- Stakeholder (students, faculty, management, ICT, etc.) views on fairness, equity, and responsibility (e.g., Chen & Zhu, 2019; Holstein & Doroudi, 2019).
- Scoping and systematic reviews on fairness, equity, and responsibility in learning analytics (e.g., Riazy et al., 2021; Vasquez et al., 2022).
- Policy and framework analysis and/or development to ensure fairness, equity, and responsibility in learning analytics (e.g., Cerratto Pargman & McGrath, 2021; Shibani et al., 2022).
- The relationships/intersections of ethics in learning analytics with fairness, equity, and responsibility (e.g., Ladjal et al., 2022; Li et al., 2022).

The call generated significant interest with 13 submissions.

2. Overview of the Special Section

Following a rigorous peer-review process, nine papers were accepted for this special section on fairness, equity, and responsibility in learning analytics. These papers provide a range of interesting, diverse, and critical views, outlined here:

- In "Amplifying Student and Administrator Perspectives on Equity and Bias in Learning Analytics: Alone Together in Higher Education," Heiser, Dello Stritto, Brown, and Croft (2023) explore levels of concern around bias and equity issues in the use of learner data with students, diversity and inclusion leaders, and administrative leadership in higher education institutions (HEIs). The main findings suggest that stakeholders have varying degrees of data literacy, leading to inequality and bias perception in the various processes of learning analytics. Heiser et al. conclude that data literacy is required for students to make informed decisions regarding the collection and interpretation of their data and highlight the need to engage stakeholders across the organizational hierarchy in decision-making to increase trust and transparency in data governance for learning analytics.
- In "Applying a Responsible Innovation Framework in Developing an Equitable Early Alert System: A Case Study," Patterson, York, Maxham, Molina, and Mabrey III (2023) discuss how early alert retention systems may amplify equity-based gaps. The authors present an anticipation, inclusion, responsiveness, and reflexivity (AIRR) framework, which was applied as an accountability tool to guide the design and development of a more equitable early-alert retention system at James Madison University.
- In "The Effects of Explanations in Automated Essay Scoring Systems on Student Trust and Motivation," Conijn, Kahr, and Snijders (2023) discuss their study on AI transparency with an automated essay scoring system with 144 participants. The study sought to explore the extent to which transparency regarding an AI grading system impacted both trust and motivation in students. Interestingly, the authors found that the extent of transparency had no significant impact on student trust. Conversely, automated grading as opposed to human grading was seen to diminish both trust and motivation when the scores given were lower than expected.
- In their article "Transparency and Trustworthiness in User Intentions to Follow Career Recommendations from a Learning Analytics Tool," Gedrimiene, Celik, Mäkitalo, and Muukkonen (2023) focus on the importance of trustworthiness and transparency in a tool that provides guidance and recommendations for career paths. To this end, Gedrimiene et al. (2023) identified three dimensions of transparency — clarity, disclosure, and accuracy — and correlated them with perceived trustworthiness. An empirical study involving 106 users showed that accuracy had a direct positive impact on the users of the tool, while clarity and disclosure were found to have no significant impact. This contribution prompts consideration about the use of learning analytics–based recommendations and the degree of trust that users should place in such career path recommendations, particularly regarding the extent to which they should be treated as advice or as imposed decisions.
- The next article in the special section — "Learning Analytics in Physics Education: Equity-Focused Decision-Making Lacks Guidance!" by Grimm, Steegh, Kubsch, and Neumann (2023b) — examines equity-focused learning analytics in physics education from multiple theoretical perspectives, including the responsibility to act and critical theory. Grimm et al. suggest a three-stage framework for achieving "equitable learning analytics" that tackles the problems of biased algorithms and discriminatory environments in education.
- "'It's like a double-edged sword': Mentor Perspectives on Ethics and Responsibility in a Learning Analytics–Supported Virtual Mentoring Program" by Lee and Gargroetzi (2023) looks at fairness, equity, and responsibility in the domain of online mentorship programs. The authors propose design recommendations for responsible learning analytics, bringing together reflections from three stakeholder groups: responsible instructors, responsible students, and responsible institutions. Lee and Gargroetzi emphasize the importance of hearing from all stakeholders in the learning analytics ecosystem to address the ethical complexities of this domain.
- The study by Swauger and Kalir (2023), entitled "Learning Analytics and the Abolitionist Imagination," presents three conceptually speculative vignettes to illustrate that learning analytics technologies can be used in ways that were not intended or expected by their designers. The authors imagine that learning analytics technologies could be re-engineered by learners for their divergent and interest-driven needs, building fairer, more equitable learning analytics ecosystems.
- In Meaney and Fikes's (2023) "The Promise of MOOCs Revisited? Demographics of Learners Preparing for University," the authors explore the behaviours of learners from under-represented backgrounds in MOOCs that have been designed to be inclusive. The authors used unsupervised machine learning techniques, clustering, and Gower and Manhattan distances to group learners based on their digital traces in the MOOCs. Meaney and Fikes examined nine MOOCs, considering demographic variables to assist in clustering. The authors found that learners without a college degree were more likely to perform well compared to college-educated learners. Learners from lower socioeconomic

backgrounds were found to be just as likely to succeed as those from middle and higher socioeconomic statuses. The authors' contribution suggests that MOOCs may provide fair and equitable spaces for under-represented learners.

- The final article — "New Vistas on Responsible Learning Analytics: A Data Feminist Perspective" by Cerratto Pargman, McGrath, Viberg, and Knight (2023) — examines data feminism from D'Ignazio and Klein's (2020) philosophy as a critical and theoretical approach in the domain of responsible learning analytics. The authors argue that there is insufficient attention paid to the epistemic, political, and economic powers that data holds in learning analytics. The article presents and proposes further discussions on bias, fairness, transparency, and privacy, viewed through the lens of data feminism's seven principles. These principles examine power, challenge power, elevate emotion, rethink binaries, embrace pluralism, consider context, and make labour visible to acknowledge the structural oppression of data science practices in learning analytics. The authors posit further implications of utilizing the data feminism approach, together with learning analytics, to revise educational programs and engage with a variety of ethical frameworks.

3. Discussion

In finalizing this special section exploring trust, transparency, fairness, and responsible learning analytics, we were gratified that the included articles responded positively to the underlying critical orientation of our call for papers. Databases and data analytics "are expressions of power/knowledge and they enact and reproduce such relations" (Kitchin, 2014, p. 22); as well, they are essentially agentic and performative (Prinsloo, 2019). In light of increasing concerns about the potential of data analytics to be shrouded in obscure systems and processes — producing unfairness, resulting in distrust and in irresponsible collection, analysis, and use of student data — this special section demonstrates that the learning analytics community does not shy away from critically reflecting on these concerns.

Although ethical and critical considerations have been integral since the emergence of learning analytics as a distinct research focus and practice, increasing attention on trust, transparency, fairness, and responsibility has emerged. Does this mean that learning analytics research has "moved on" and that ethics as a specific concern is no longer in vogue? No empirical evidence suggests that ethics — as a specific concept, orientation, and practice — is receiving less attention in learning analytics research. This special section possibly heralds a move toward considerations of trust, transparency, fairness, and responsible learning analytics as very practical and actionable forms or elements of ethics. Education has provided researchers with access not only to more data than ever before, but to more nuanced, granular data, creating reasonable grounds to consider what ethical learning analytics will look like in future. The increasing collection and combination of a variety of forms of data — and data sources — across platforms and devices, the platformitization and commercialization of learning platforms, and the deployment of generative artificial intelligence raise not only new concerns (Prinsloo et al., 2023), but also new questions about trust, transparency, fairness, and responsible learning analytics.

While it would be unfair to attempt a thematic analysis of the selected articles in this special section, the following two issues seem to be recurring themes. The first is the role of various stakeholders in ensuring trust, transparency, fairness, and responsible learning analytics (Heiser et al., 2023; Lee & Gargroetzi, 2023). The other, more surprising element is the role of accountability in ensuring trust, transparency, fairness, and responsible learning analytics. For example, Patterson et al. (2023) share their development of the AIRR framework designed on the basis of anticipation, inclusion, responsiveness, and reflexivity. The issue of accountability is also linked to transparency and trust (e.g., Conijn et al., 2023), the dimensions of which, in the article by Gedrimiene et al. (2023) are explored as clarity, disclosure, and accuracy and correlated to perceived trustworthiness.

A leitmotif in the articles here (whether implicit or explicit) is learning analytics as an expression of power that enacts and reproduces existing inequalities and unfairness, or naturalizes new forms of injustice and unfairness. Grimm et al. (2023b) explore a selection of theoretical positions such as the obligation to act and critical theory that link well with Cerratto Pargman et al.'s (2023) exploration of data feminism.

Two articles in this special section move, in different ways, beyond critique: Meaney and Fikes (2023) provide evidence that well-designed learning can provide equitable experiences for students at the margins; Swauger and Kalir (2023) "move away" from theory and/or empirical research through three speculative vignettes.

4. (IN)Conclusions

Is this special section the final word on trust, transparency, fairness, and responsible learning analytics? Anything but. Does this special section herald a "new beginning"? Certainly not. If this special section is neither the end nor the beginning, what is it then?

If data is power, then the collection, analysis, and use of student data can be in the service of trust, transparency, fairness, and responsible learning analytics, or, contrarily, serve to exclude and further marginalize through obscure systems and processes. Having said that, we should stop thinking in terms of binaries — good or evil, fair or unfair, and so forth. Much more productive is to consider the nuances in fairness and/or injustice, to reflect on unintended consequences, and on how unfairness is just a 1 or a 0 away.

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