JOURNAL OF LEARNING ANALYTICS

SOLAR SOCIETY for LEARNING ANALYTICS RESEARCH

Volume 10(1), 133–148. https://doi.org/10.18608/jla.2023.7781

# New Vistas on Responsible Learning Analytics: A Data Feminist Perspective

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**Abstract**

The focus of ethics in learning analytics (LA) frameworks and guidelines is predominantly on procedural elements of data management and accountability. Another, less represented focus is on the duty to act and LA as a moral practice. Data feminism as a critical theoretical approach to data science practices may offer LA research and practitioners a valuable lens through which to consider LA as a moral practice. This paper examines what data feminism can offer the LA community. It identifies critical questions for further developing and enabling a responsible stance in LA research and practice taking one particular case — algorithmic decision-making — as a point of departure.

**Notes for Practice**

- Ethical considerations in learning analytics research and practice are addressed through two main research strands with different foci. The predominant strand focuses on procedural elements of data management while the other focuses on learning analytics as a moral practice.
- Responsible learning analytics embraces these two strands but goes beyond them as it also seeks an understanding of where learning analytics should (and should not) be deployed, for whom and why.
- Data feminism is a critical approach to data science and learning analytics research and practices.
- Considering data feminism's central tenets may offer new vistas on responsible learning analytics for both researchers and practitioners.

**Keywords**

Data feminism, critical theory, ethical guidelines, learning analytics, responsibility

**Submitted:** 25/06/2022 — **Accepted:** 08/02/2023 — **Published:** 10/03/2023

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## 1. Introduction

A decade ago, Ferguson (2012) called on the learning analytics (LA) community to develop and apply ethical guidelines to ensure that LA scholars and practitioners undertake responsible approaches when designing, deploying, and using LA systems. Since then, many frameworks, checklists, and evaluation methodologies have emerged to address ethical and moral considerations of LA system development and interventions. These include, among others, the socio-critical ethical framework (Slade & Prinsloo, 2013), a set of design guidelines (Pardo & Siemens, 2014), the DELICATE ethics checklist (Drachsler & Greller, 2016), JICS's code of practice (Sclater & Lally, 2016), the SHEILA (Supporting Higher Education to Integrate Learning Analytics) policy framework (Tsai et al., 2018), and the more recent global guidelines for the ethics of LA (Slade & Tait, 2019). As LA systems evolve and become more technically sophisticated, including recent developments in AI (Buckingham Shum & Luckin, 2019), their further design and use in education contexts bring new questions into focus. Algorithmic decision-making and machine learning, for example, prompt questions about oversight and the prevention of harm, algorithmic accountability, student vulnerability, agency, and the erosion of student–teacher relationships (Slade & Prinsloo, 2013). Baker and Hawn (2022) have offered a list of general strategies and specific recommendations for reducing algorithmic bias in education; they relate to improvements in data collection, improvements in tools (e.g., LA systems) and resources, the creation of structures to incentivize openness, and the broadening of community.

Notably, we see these strategies as necessary but not sufficient to enable us to perform responsible LA practices since AI tools have the potential to become increasingly autonomous in their functionality and decision-making processes. AI has the potential to reify existing systems and separate humans from decisions through autonomous processes. Consequently, the question of who becomes accountable and responsible for decisions made by an AI tool used in education is critical. Thus, while these efforts are central to higher education institutions' development, acceptance, and adoption of LA tools and practices, a systematic review of empirical LA ethics work indicated a mismatch between the most common ethical frameworks used in LA and the kinds of moral and ethical issues identified (Cerratto Pargman et al., 2021). These issues included misuse of platforms (Adejo & Connelly, 2017; Howell et al., 2018), the potential for increased bias (Klein et al., 2019), moral discomfort (Jones, 2019a), and ethical dissonance (Jones, 2019b). This mismatch represents a gap in practicable approaches to matters of justice and care in education, rather than transparency, privacy, and informed consent, which are the areas most often focused on in research about ethics in LA.

This claim is echoed in a range of concerns raised about ethical frameworks. For example, Whittlestone et al. (2019) identify three main concerns in the context of artificial intelligence (AI), but also with relevance to LA frameworks, namely: 1) the lack of clarity and use of ambiguous definitions of ethical concepts; 2) insufficient attention to conflicting tensions between values; and 3) insufficient evidence on technological capabilities, societal impacts, and needs. Similarly, Kitto and Knight (2019) underscore that 1) practitioners often do not adhere to the checklists, frameworks, and evaluation methodologies, 2) data regulations, such as the General Data Protection Regulation (GDPR), are challenging to apply in LA, and 3) tensions and gaps exist in LA checklists and frameworks for supporting trusted, ethical development. The sheer number of LA ethical guidelines contributed by higher education institutions seems to reflect the need for contextual consideration but also suggests that the ethics of these systems remains "up for grabs" (Greene et al., 2019, p. 2122); in part, because "It is not clear by whom and how the ethical implications of learning analytics will be assured" (Prinsloo & Slade, 2017b, p. 55). Indeed, LA scholars have recently stressed that very few practical implementations of ethical LA frameworks in education settings yet exist (Ladjal et al., 2022).

The data feminism (DF) approach is of interest to the LA community as it contributes a set of critical principles that questions the epistemic, political, and economic power entrenched in the so-called "objective," "neutral," "scientific" data, and the discourses about it (D'Ignazio & Klein, 2020). Such principles echo the need to embrace critical perspectives to discuss the risk that LA practices could lead to exacerbating existing inequities in education (Wise et al., 2021), and the impact that LA in practice may have on "the cognitive, emotional, and social well-being of learners in the context of broader social structures" (Ochoa et al., 2020, p. 1). DF has the potential, in this respect, to offer the LA community a conceptual lens to support LA's increasing cognizance and social responsibility for its own epistemic, educational, and sociocultural consequences.

This paper seeks to generate a critical reflection on responsible LA. Towards that goal, we examine the implications DF principles may have for understanding and contributing to defining and enabling responsible LA practices in education. The paper considers DF's implications on LA practices and research by identifying several central questions (see Section 3.2 and Table 1). The paper is structured in the following way. First, we discuss the "responsible lens" to analyze ethical principles. We synthesize several ethical areas and considerations across a range of central ethical frameworks and guidelines contributed hitherto by LA scholars and practitioners. Second, we distinguish two strands of attention in ethical LA principles and frameworks. Third, we introduce the central tenets of DF (D'Ignazio & Klein, 2020), present a brief overview of the critical DF principles and several main concerns related to LA practices and research. Finally, we conclude by identifying the implications of the DF principles for the design and deployment of LA systems through one particular case; algorithmic decision-making.

## 2. A Responsible Lens for the Analysis of Ethical Principles in LA

From its beginning, the LA community has been concerned about the responsible use of LA tools and has sought to understand the risks and potential harms associated with data-driven practices, the underpinning models, algorithms, and assumptions about how students learn (Siemens, 2013). Such concerns have been reflected in the ever-increasing number of publications on ethics that have contributed to the LA field in the last decade. LA scholarship focuses on ethical issues that comprise mostly conceptual work, but there is also emerging empirical work (Cerratto Pargman & McGrath, 2021). Within the conceptual work, we identify research efforts focused on the design of ethical frameworks, guidelines, and codes of practice (Drachsler & Greller, 2016; Engelfriet et al., 2015; Pardo & Siemens, 2014; Sclater, 2016; Slade & Prinsloo, 2013; Slade & Tait, 2019; Tsai et al., 2018).

Dealing with ethical considerations in practice is complex due to the context in which such concerns (may) arise and the inherent complexity of the current educational landscape, characterized by multiple stakeholders involved and the rapid pace of Edtech development. To conceptualize LA's ethical and moral dilemmas in higher education, Slade and Prinsloo (2013), Prinsloo & Slade (2018), and Khan et al. (2018) stress a need for a holistic understanding of the myriad ethical issues that arise throughout the LA lifecycle. Such a view echoes Buckingham Shum's (2012) understanding of responsibility and ethics in LA: "In the context of learning analytics, every step of the lifecycle — from data to analytics to insight to intervention — is infused with human judgment" (Buckingham Shum, 2012, p. 8).

From this integrative point of view of ethics and human judgment, Prinsloo and Slade (2018) explore the meaning of responsibility in LA and introduce the distinction between *being responsible* and *being response-able* as a way to connect human responsibility with the capacity to act and not only with being "accountable," and "answerable" (p. 3). Further, Prinsloo and Slade (2018) underscore the difference between being "responsible" in the sense of being transparent and being "response-able," meaning able to act based "on the fiduciary duty of higher education, and the reality and impacts of the asymmetrical power relationships between higher education and students" (Prinsloo & Slade, 2017a).

## 2.1. Two Strands of Attention in LA Ethical Principles

In line with Prinsloo and Slade's (2018) reasoning, we identify two strands of attention in the ethical principles suggested in central and complementary LA ethical frameworks and codes of practice (Cerratto Pargman & McGrath, 2021). One strand focuses on procedural elements of data management and accountability. The other focuses on the duty to act and LA as a moral practice corresponding to response-ability.

The *first strand* relates to responsible LA in accountability (Prinsloo & Slade, 2018). It relates more specifically to how universities and researchers answer and are accountable vis-à-vis the management of educational data and the analytics involved. This strand focuses predominantly on elements of data management and includes issues related to transparency, privacy, informed consent, and validity.

The *second strand* focuses on value-oriented ethical considerations related to why the data should be used and under which circumstances institutions are responsible for such use. This strand focuses on being response-able (Prinsloo & Slade, 2018) and on the institutional obligation or duty to act (Ferguson, 2019; Ferguson & Clow, 2017; Prinsloo & Slade, 2017a). Issues addressed in this second strand include 1) the obligation to act, 2) enabling interventions, and 3) minimizing adverse impacts.

These strands differ in their foci and ultimate purpose. The first is predominantly interested in institutional data and committed to being accountable for and complying with the legal considerations when deploying LA systems. The second, in contrast, seeks to mobilize institutional action and is committed to acting according to the institution's ethical and moral compass. Yet, they also share common traits and build, albeit indirectly, on a set of normative ethical principles that emerged after the Second World War, with an increased awareness of how biomedical and behavioural research should be conducted. Both the Belmont report of 1978 (Willis et al., 2016) and Beauchamp and Childress (2001) identify central and overlapping principles for conducting bio-ethical and behavioural research: *respect for autonomy*, *beneficence*, *non-maleficence*,[1] and *justice.* These principles are often held in tension, for example, where benefits are most likely derived from complete data (beneficence) that would be unlikely to be achieved via explicit consent processes (autonomy). Similarly, ethical principles developed within LA are often in tension, with dilemmas across the design, deployment, and use of LA systems (Kitto & Knight, 2019).

## 2.2. Shifting from Individual Ethics to Structural Power Differentials

More importantly, the current set of normative ethical principles applied in LA reflects that the cause of any ethical problem is understood to be found either in "individuals or computer programs" instead of the socio-technical practices that emerge and develop in the context of "structural power differentials" (D'Ignazio & Klein, 2020, p. 60). Such power differentials protect privileges, for example, in educational programs with historical gender imbalances (Ford & Wacjman, 2017). Another example is college admission cases that exemplify protecting privilege mechanisms, particularly in the USA (The New York Times, 2019). From this understanding of ethics in LA, bias in the design or use of LA systems reflects wider structural power differentials that must be considered through the LA lifecycle rather than via individual ethical decisions made by developers (or stakeholders) and the instantiation of ethical principles into LA programs.

Accepting that bias is a symptom of a "structural oppression" (D'Ignazio & Klein, 2020, p. 63) encourages us to turn our attention to the "systematic nature of unfairness that has long been perpetrated by certain groups on others" (p. 62). On this note, D'Ignazio & Klein (2020) refer more specifically to oppression by explaining that it "happen[s] when power is not distributed equally — when one group controls the institutions of law, education, and culture and uses its power to

[1] Note that in the Belmont report, "Beneficence" is mentioned, and the report distinguishes between doing good and doing no harm. Beauchamp and Childress articulate these as distinctly different principles.

systematically exclude other groups while giving its own unfair advantages or simply maintaining the status quo" (p. 8). The authors discuss the combination of structural oppression with structural power and privilege in terms of the "matrix of domination," a concept introduced by Patricia Hill Collins (1990). Following D'Ignazio and Klein (2020; see Table 1), the matrix of domination operates via structural power that organizes oppression via laws and policies; the disciplinary power exercised via implementing and enforcing the laws and policies; the hegemonic power via circulating oppressive ideas through culture and media, and the interpersonal power via individual experiences of oppression. Focusing on standard data science practices, D'Ignazio and Klein (2020) suggest examining how such practices reinforce existing inequalities and call for using data science practices to challenge and change the distribution of power, and a privilege most often enmeshed with structural oppression in significant sectors of societies. Education is one of these significant sectors where standard data science practices associated with the development, design, deployment, and use of LA systems constitute a specific case to be critically scrutinized.

Against this background, we argue that responsible LA requires awareness of both these strands of attention (i.e., on data accountability and value-laden considerations) and goes beyond them to question the data science practices valued and legitimized in LA, with the goal of contributing to equitable and socially just LA practices. Our work also seeks an understanding of where LA should (and should not) be deployed and LA's positions in reinforcing or challenging wider systems. As we outline further in the following section, responsibility in LA practices may benefit from drawing on data feminism (D'Ignazio & Klein, 2020). In doing so, we hope to stimulate discussion regarding the reframing of these two strands away from the question, "How do we do LA well?" to instead ask, "How should we act socially responsibly, and what is the role of LA in that?"

## 3. Data Feminism: Central Tenets

Data feminism (DF; D'Ignazio & Klein, 2020) is a critical approach to standard data science practices. Grounded in critical feminist theory, D'Ignazio and Klein (2020) scrutinize data science practices by critically studying how historically such practices have operated, the drivers, the methods, the models, and the visible actors involved. DF brings together two aspects of feminism of particular value for the LA community. On the one hand, DF demonstrates an alternative, possible way of "thinking about data, their analysis, and how they are presented, that is informed by the tradition of feminist activism" (D'Ignazio & Klein, 2020, p. 3). On the other hand, DF is informed by the legacy of feminist critical thought and, more specifically, the development of feminist social science that has questioned the "traditional science's aspirations to be value-free" (Bardzell & Bardzell, 2011).

In their work, D'Ignazio and Klein (2020) view data as an expression of epistemic, political, and economic power structures. This is a consequence of understanding "that society is structured by power relations that generate unequal social locations; one location is occupied by members of the dominant group, and other locations are inhabited by members of subordinate groups" (Wood, 2009, p. 1). But D'Ignazio and Klein (2020) underscore that DF is "not only about gender"; "it is also about how race, class, sexuality, ability, religion, age, and geography, among other factors," intersect and influence people's experiences and opportunities in the world (p. 14). This way of reasoning firmly criticizes educational discourses (e.g., data-driven educational practices) in which the value of the student data is related to its intrinsic quality of being "objective," "neutral," and "scientific." In this respect, Wise et al. (2021), for example, problematize the "objectivity myth" that aims to question the neutrality of LA data and measures that are taken for granted in the "premise that data collected about learners and learning can provide a sound basis for making decisions to improve learning processes and outcomes" (p. 641). A corollary of this stance is that a responsible approach in LA needs to assist researchers and practitioners further to develop awareness and act upon the fact that student data is never raw but a result of socio-technical construction: "a site of political, social, and historical forces" (Wise et al., 2021, p. 641).

D'Ignazio and Klein pay specific attention to "how standard practices in data science serve to reinforce" existing inequalities and how to "use data science to challenge and change the distribution of power" (D'Ignazio & Klein, 2020, pp. 8–9). By situating data science practices in a larger historical and cultural context, for example, the authors help us understand that some situations — like online invigilator systems not being able to detect the face of a student of colour, or associating someone's muscular twinges with suspicious behaviour (i.e., cheating) during a digital examination — speak of a broader socio-technical pattern and not an isolated technical incident. In this sense, examining the technical fairness of the algorithms implemented in the invigilator system does not go to the root of the problem. Invigilator systems that do not recognize students of colour or students with disabilities are the product of data science practices that reinforce existing inequalities.

In the same way, scholars — including data scientists and information systems researchers — can mitigate the structural oppression of certain groups through their socio-technical practices and challenge power. Here, D'Ignazio and Klein (2020) refer, for instance, to the "Local Lotto" Project (2012–2015) that "taught local high school students statistics and data analysis rooted in neighbourhood and justice concerns" (p. 68; see also Deahl & Rhie, 2013). The project attempted to help predominantly Latinx and Black students use maths and statistics to analyze data relevant to them and their neighbourhood. By doing so, the students in the program experimented with gaining agency in matters of social justice by challenging privilege and power in society.

These commitments are of interest to LA. They invite us to revisit past conversations about what data practices are accepted in LA, why, and for which educational purposes, along with what constitutes a stakeholder, and which groups of students (in terms of race, class, sexuality, ability, religion, age, and geography) are considered in discussions about ethics and LA data practices. Against this background, the following section presents data feminism's seven core principles, preceded by a note on research reflexivity and the methodology applied.

### 3.1. Methodology and Research Reflexivity

In search of broadening our understanding of ethics in the setting of LA, we looked for concepts and frameworks within and outside the LA community that could help us to reflect on the boundaries of the current discourse on ethics regarding emerging LA systems. Slade and Prinsloo's (2013) socio-critical foundational framework inspired this paper and was our first candidate to apply it in our readings on the ethics of LA; however, while this ethical framework contributes to considering "the role of power, the impact of surveillance, the need for transparency, and an acknowledgment that student identity is a transient, temporal, and context-bound construct" (p. 1510), it proposes six central principles to help higher education institutions act on the ethics of LA systems *after the fact*.

The choice of data feminism's principles aligns with our ambition to further develop the socio-critical perspective on LA and contribute to a critical discussion on the ethics of LA system design from a socially responsible stance. This stance is shaped by our backgrounds in human–computer interaction, education sciences, information systems, philosophy, psychology, and cognitive psychology, which led us to engage with LA systems as socio-technical arrangements made by and for specific groups of people. Our research positionality is related to how we view LA systems through the learning and teaching practices that LA systems configure, but also the socio-technical practices and design narratives that presently envision and develop LA systems. Notably, our discussions on responsible LA relate to questions like these: How should we, as researchers, practitioners, and teachers working with LA systems in Europe and Australia, act responsibly? What is the role of LA in that? What is the bottom line of our duty to act in LA? And where does our individual responsibility start and end in relation to our institutional roles as practitioners, designers, researchers, or others?

Those questions guided our critical reading of DF principles and were specified (see Table 1) throughout conversations that started almost two years ago in the LA setting. Although each author connected with DF principles differently due to our identities, disciplinarity, power, and privileges in society, we approached D'Ignazio and Klein's piece (2020) critically and with the ambition to deepen our understanding of what the data feminist lens could contribute in our search for a shared understanding of responsible LA.

### 3.2. Data Feminism Principles

This section presents DF's seven principles, identifies how these are relevant to LA practices, and poses critical questions to the LA community based on these principles (elaborated in Table 1).

**Table 1:** Critical Questions to the LA Community

| Principles | Questions for LA |
|---|---|
| **Examine power** | Whose voices are predominantly represented in LA practices? Whose interests and goals and what learning do we prioritize? How do the different stakeholders value collecting, analyzing, and using student data in education? How is such a value created, legitimized, and accepted by the various stakeholders? Which conflicts arise among the stakeholders involved in LA? What epistemological and ontological tensions exist regarding student data and learning assumptions in LA? |
| **Challenge power** | Which understandings and perspectives of social justice are embedded in LA practices? Which student groups (or teachers) are inadvertently oppressed by using LA systems in higher education? How do LA practices unintentionally exacerbate existing inequities in education? What are the assumptions regarding the power of socio-technical systems in complex educational practices in LA? How is the agency or "charisma" (Ames, 2019) of LA systems configured throughout LA data science practices? |

| | |
|---|---|
| **Elevate emotion and embodiment** | Whose learning is considered in learning analytics systems and practices? How does data represent the complexity of the learning experience? How does learning analytics reduce or obscure the human side of the data? How may data be represented and LA designed to capture such complexity? How is student failure contemplated in LA as a natural step in the learning journey? How do stakeholders respond to LA as persuasive, emotive, and uncertainly evaluative? |
| **Rethink binaries and hierarchies** | Who are the students using LA systems, and how do LA data science practices account for them? Which are the specific data categories to count, classify, and represent? How accurate are they, and for which purposes are these categories necessary? Which groups are missing from the classified datasets and why? Who is involved in categorizing students? What is the purpose of such classification for using LA systems in education? What are the LA assumptions behind applying binaries and hierarchies in student data? How are ambiguity and opacity in data addressed in LA practices? How do we collect (or refuse) data and recover and forget data in ways that support learning and recognize changing contexts, values, and behaviours? Who is held accountable, or not, by the data we collect? |
| **Embrace pluralism** | Which conflicts of interest prevent understanding the collected data's specific context? Whose ethics is referred to when speaking of complying with ethical principles in LA? How can the LA community stimulate practices around reflexivity and discussions about co-liberation via data in user-centered participatory methods? How can the data be interpreted and reinterpreted by stakeholders across different contexts? |
| **Consider context** | What education contexts are targeted? What are the specificities of the targeted contexts that should be accounted for when generalizing results and transferring LA solutions from one context to another? Are there any specific values (e.g., in terms of understanding privacy, collaboration, or educational values) to pay attention to? How do we work with these values in the LA design process? |
| **Make visible labour** | Whose data work is acknowledged in LA practices? Whose work is not valued or credited and why? What labour and value are lost in adopting LA approaches? What work is required to support stakeholders in their design, implementation, and use of LA, including teacher data literacies and new forms of support for students, which may require a certain level of feedback literacy on the part of the teacher? |

**Principle 1: Examine power** focuses on identifying and analyzing "How power unfolds in and around data" (D'Ignazio & Klein, 2020, p. 24). This principle examines the structural, disciplinary, hegemonic, and interpersonal domains to understand the "current configuration of structural privilege and structural oppression." For instance, D'Ignazio and Klein point to examples in facial recognition software, where analysis of their application and underlying datasets reveals significant racial biases. Such an example points to many decisions made by people in positions of power and privilege for whom issues regarding race, gender, class, and ability are "other people's problems" (p. 31). Such socio-technical decisions exposed in using facial-recognition software by people with dark skin illustrate how power operates through data science practices and how some groups benefit from data science practices while others are disproportionally harmed.

In LA, this principle comes to question who sets the goals in the development of LA systems (some of them including facial-recognition software); which and whose goals are overlooked; who benefits from the use of LA and how; who does not; and how bias can be addressed at its source.

**Principle 2: Challenge power** "requires mobilizing data science to push back against existing and unequal power structures and to work toward more just and equitable futures" (D'Ignazio & Klein, 2020, p. 53). D'Ignazio and Klein (2020) mention, for instance, compiling counter data in the case of missing datasets or institutional neglect; auditing opaque algorithms and holding institutions accountable; bringing dominant groups and minoritized groups together to work toward their mutual liberation; cultivating the next generation of data feminists as examples of how to challenge power via data science practices. D'Ignazio and Klein (2020) refer to Benjamin's (2019) concept of "imagined objectivity of data and technology," which highlights the role that cultural assumptions and preconceptions play in beliefs, such as that datasets and algorithms are less partially objective and discriminatory than people. On this note, D'Ignazio and Klein (2020) emphasize that challenging power via DF would instead question the core of the problem and act consequently rather than discuss flawed individuals/groups or seek technological fixes to discriminatory datasets or algorithms. It would also start acknowledging the historical, political, and cultural developments that make groups of people arrive at the present with different power and privileges.

In LA, this would translate into considering disabled, immigrants, people of colour, non-binary students, and teachers, to name just a few, when designing socio-technical interventions that target equity and social justice and not necessarily equality (cf. D'Ignazio & Klein, 2020, see p. 62).

**Principle 3: Elevate emotion and embodiment** underscores the value for data science practitioners to consider multiple forms of knowledge, including individuals' feelings and affections, viewing them as legitimate constituents of knowledge (D'Ignazio & Klein, 2020). Elevating emotions and embodiment means several things: 1) considering emotion and affection to balance understandings of data commonly considered products of purely rational practices, and 2) acknowledging that data practices are situated, relational, and constantly developing from a particular worldview anchored in the human body (D'Ignazio & Klein, 2020). This principle speaks to the visualization practices data scientists, who are often unaware of multiple sensory formats of presenting data or the point of view, standpoint, or positionality reflected in maps, charts, or any other visual representation of data. More importantly, it points to the relationship between people's feeling bodies and how knowledge is constructed and communicated. On that note, the authors provide multiple visual, visceral examples to argue their case that neutrality in data representation is practically impossible. D'Ignazio and Klein (2020) are explicit about the absurdity and harm embedded in beliefs such as universal objectivity, and underline that "rather than viewing these positionalities as threats or as influences that might have biased our work, we embraced them as offering a set of valuables perspectives that could frame our work" since they can generate creativity and wholly new research questions (p. 83). From this point of view, what matters in a socially just design process is to look for those at the margins and ask what our social systems reproduce and legitimize in the education sector, and what are they trying to exclude and why (see Bardzell, 2010).

This principle encourages LA researchers to look at how data are represented and communicated via, for instance, LMS dashboards or other interfaces shaping academic knowledge about students. This principle can be considered when designing and evaluating relevant LA interventions, especially where many different types of students do or could participate.

**Principle 4: Rethink binaries and hierarchies** aims to challenge binaries such as gender, race, and other classification or counting systems. Here, the intersectional approach underpinning DF is most present. D'Ignazio and Klein (2020) discuss the complexities and nuances of creating knowledge and data visualization practices that classify individuals into a single category or dimension. Referring to Seager's (2016) maxim that "what gets counted counts," the authors underscore the power of conceptual and computational categories in classifying, excluding (becoming invisible), or misclassifying the population it intends to represent. Yet, outdated, narrow, simple classificatory categories are those used by policy-makers or officers allocating resources. In this sense, classification systems can be tools for both oppression and liberation, depending on how they are used, who is doing the classification, and whose interests they are serving (Klein & D'Ignazio, 2020). This is tricky because, as Bowker and Star (2000) put it, classification systems are essential for any working infrastructure, and categories in such classification systems tend to become naturalized, invisible, accepted, and taken for granted until they break down. They are often not questioned, as they embed authority and come with scientific, neutral, or value-free labels. However, such classification systems are constructed by and for people, always with a purpose in mind, and they often "carry significant material consequences" for people (Klein & D'Ignazio, 2020, p. 104).

This principle speaks directly to intersectionality in LA practices by questioning how student data are classified and interpreted. For example, what categories are predictive modelling systems that suggest career paths and programs to "students with disabilities" or "immigrant" or "first-generation students"? How do predictive algorithms interpret these categories? What does the educational institution do with the knowledge gained about its students? Will they allocate more or fewer resources to programs with the most students having a medical diagnosis? Why? Yet, "counting is always complicated. But undertaken deliberatively, tailored to specific goals, and with privacy issues and potential harms always in mind, counting can support accountability — as one method, among many, of working toward a larger goal" (Klein and D'Ignazio, 2020, p. 122).

**Principle 5: Embrace pluralism** "reflects a key tenet of feminist thinking, recognizing that a multiplicity of voices, rather than one loud or technical or magical one results in a complete picture of the issue at hand" (D'Ignazio & Klein, 2020, p. 136). Nevertheless, this principle does not mean that anything goes and all perspectives have equal weight. It instead suggests that the different perspectives that contribute to a data project come from somewhere (Haraway, 1988), and that "when people make the knowledge, they do so from a particular standpoint, from a situated, embodied location in the world" (D'Ignazio & Klein, 2020, p. 136). The assumption is that pluralism is a principle that in data science can contribute to a richer, more robust understanding of an issue. This principle is explained through the data scientist's *reflexivity,* and engagement in *co-liberation* practises, both considered means to embrace pluralism.

*Reflexivity* entails being transparent about the methods applied and the identities of those engaged in the project (D'Ignazio & Klein, 2020). Reflexivity also entails explaining how those involved classify, count, or analyze data related to the project from a professional position and their power in treating this data. In LA, this reads as follows: those involved in analyzing and interpreting student data, operating under the principle of pluralism, would be invited to be transparent about the datasets used, their sources, possible combinations with other datasets, as well as methods and tools to classify, clean, and interpret the data.

*Data co-liberation* practices "require that those technical workers [doing data science] acknowledge that they are engaged in a struggle for their liberation as well, even and especially when they are members of dominant groups" (D'Ignazio & Klein, 2020, p. 141). Co-liberating practices resonate with participatory design practices, how they have been configured in LA, and how they can further develop toward decolonizing LA practices and tools, as well as cultivating community solidarity in data work. On this note, a recent review on participatory and co-design practices shows that even though a growing number of LA scholars have used participatory methods in recent years, the selected literature often describes the participatory design activities superficially, seldom considering the process description (Sarmiento & Wise, 2022). Including stakeholders to help other stakeholders raise their voices is not enough, as co-liberation practises entail stakeholders working together to challenge (political, economic, and social) power embedded in data science practices.

Inspired by the example of digital democracy described in D'Ignazio and Klein (2020, p. 144), and in Axelsson & Mienna (2020) regarding Indigenous data sovereignty and policy in Sweden, one implication for LA could be working with Indigenous groups to understand what student data is necessary to produce about their community in order to support learning in an inclusive, pluralistic educational sector.

**Principle 6: Consider context** asserts that considering the specific situation of the accessed data is essential for conducting accurate, ethical analysis. Data is thus not seen as neutral or objective but always configured and shaped by social relationships. Data are never raw but "fully cooked" already when beginning a research project (see Gitelman & Jackson, 2013). This principle challenges data scientists to interrogate where their data comes from and its limitations and validation. For example, Simon Buckingham Shum (2018) also underscores the role that data play in emerging knowledge infrastructures that constitute the context of where the student data of LA systems are produced and valued. From a DF perspective, considering context demands understanding the social, political, and economic conditions in which data have been generated and their possible combinations with other datasets. Yet, it also requires understanding the power differentials that make up data as "data cannot speak for themselves" (D'Ignazio & Klein, 2020, p. 171).

Although considering the context in LA data science practises is not entirely new, approaching context in relational, data feminist terms is. In LA, paying attention to the context of the student data from a DF understanding would, for example, mean considering and questioning the categories used to classify the data, the data sources, the educational conditions in which they were gathered, for which educational purpose, by whom, and who is doing the counting. It would also ask those managing the data to be transparent about their positionality and consider engaging in co-liberation practises. On this note, LA scholars have also recently outlined a need to focus on the contextual nature of privacy regarding the use of student data in education (see, e.g., Mutimukwe et al., 2022).

**Principle 7: Make labour visible** underscores that data science work is the work of many hands. The work of those collecting, cleaning, analyzing, storing, classifying, and training datasets need to be visible so they can be valued and credited. In particular, D'Ignazio and Klein (2020) pay attention to the data labour that makes data science practices work and is seldom recognized as central to the data science machinery; for example, in crowdsourcing recommendation algorithm improvement (at Netflix) or in human monitoring of "automated" voice assistant responses (at Amazon Echo; see Crawford & Joler, 2018). As education institutions collect "higher volumes [and] a great variety and granularity of student data, often in real-time" (Prinsloo, 2020, p. 1), a central question regards the tension between contributions of student data to university warehouses, the knowledge that universities can gain from it, and the potential benefits of such data for student learning.

Making data labour visible in LA and the education sector points to understanding the multiple tensions in the education data supply chain (i.e., who does the work and benefits from it; Colonna, 2022). It also entails asking higher education institutions questions about the visible and invisible costs involved in the datafication of their practices.

The seven DF principles and related questions presented above provide a point of departure for reflection on how standard data science practices unfold in LA, what educational knowledge they configure, and how they contribute to equity and socially just education. To better situate what may be learned from the DF approach in the field of LA, we now turn to the specific case of algorithmic decision-making to illustrate not how each of the principles can be applied separately, but how such principles can be considered *"en masse."* The case of algorithmic decision-making helps situate some of the implications of DF for LA systems research and practice.

## 4. Implications of Data Feminism for LA Research and Practice

Since the foundation of the LA field, algorithmic decision-making (ADM) systems are of particular interest to LA as they "become an integral part of the broader research agenda at the intersections of learning, media, and technology" (Prinsloo, 2020, p. 3). Systems such as automated grading assessment, facial recognition software in online invigilators, personalized learning, and predictive modelling are compelling as they have generated much debate about fairness (Holstein & Doroudi, 2019), trust (Dietvorst et al., 2015), accountability (Kitto & Knight, 2019), values (Chen & Zhu, 2019), algocracy (Prinsloo, 2020), but also impact student/teacher well-being, opportunities, free expression, and civil rights (Center for Democracy &

Technology, 2019). Because ADM systems and associated educational practices are still emerging and open to discussion, they constitute an excellent example to reflect on what DF can contribute to discussions about responsibility and social justice in LA. In this vein, we suggest three implications for reconsidering standard data science practices in LA.

### Implication 1: Whose power to challenge in LA data science practises?

From a DF perspective, issues about bias, fairness, transparency, and privacy, which are most often discussed in relation to the development and use of ADM systems in education, while important, fall short in challenging the structural power and privilege embedded in the data science and institutional practices associated with these systems. In this respect, ADM systems must be questioned and challenged in the context of LA research, particularly "within those systems that give them meaning and animate them" (Dourish, 2016). This leads to discussions about the power of systems such as ADM via the lens of domination in the education/academic sector. Such a discussion confronts us with difficult questions regarding the historical development of an education system that has embraced "eurocentrism" as the "hegemonic perspective of knowledge" (Quijano & Ennis, 2000, p. 542) based on the following foundational myths: "first, the idea of the history of human civilization as a trajectory that departed from a state of nature and culminated in Europe; second, a view of the differences between Europe and non-Europe as natural (racial) differences and not consequences of a history of power" (Quijano & Ennis, 2000, p. 542). Considering this understanding, it is fair to ask this key question: Whose voices are structurally privileged and in power in LA data science practises?

In terms of the stakeholders involved, the presence of researchers (i.e., predominantly computer science, information systems, educational technology, human–computer interaction), edtech global corporations, policy-makers, institutional leadership, regulators, and powerful international organizations such as UNESCO, among others (most located in the Global North) are today the most powerful voices in LA. Other voices, such as those from student or teacher unions or networks such as Design Justice (Costanza-Chock, 2020), Data for Black Lives (D4BL[2]), All Tech is Human,[3] Global Indigenous Data Alliance,[4] and other initiatives representing minoritized groups of people and communities in the world — or those with direct experience of injustice in education — are less represented in LA. From a DF point of view, collaborating exclusively with groups of stakeholders already in power is problematic because recognizing a "multiplicity of voices, rather than one loud or technical or magical one" promotes real understanding (D'Ignazio & Klein, 2020, p. 136). Also, if educational institutions have a duty to act regarding the knowledge they gain from their LA data science practises, it would be fair to ask if the processes ensuring the allocation of resources check for silences in the data collected or missing datasets. "Exploring and analyzing what is missing from a data set is a powerful way to gain insight into the cooking process — of both the data and the phenomenon it purports to represent" (D'Ignazio & Klein, 2020, p. 160). Collaborating with groups of minoritized students or communities would help to get a more complete and solid understanding of how resources should be allocated among students.

Similarly, it would be necessary to investigate which tools and methods for considering the context of the data extracted are used in the data practices involved for developing systems like ADM to assess students, personalize learning or predict particular career paths. In this respect, and precisely in the context of AI in education, Howard et al. (2022) suggest the concept of "educational data journeys" to explain a framework aimed at tracing "the interrelationship between data work, power, identities, and literacies" (p. 2). Tools such as "data biography" (Krause, 2019), consisting of a short note describing the history of the data set organized around questions like these: Where does the dataset come from? Who collected it? When? How was it collected? and Why was it collected? Or "datasheets for datasets" (Gebru et al., 2021), consisting of short documents (three to five pages) that describe how the dataset was created and collected, what data might be missing, if data were preprocessed, and how the data set will be maintained. Any ethical or legal considerations important to highlight (D'Ignazio & Klein, 2020) are concrete examples of tools that could contribute to more rich and transparent data practices in LA.

In this sense, considering power in LA would entail bringing together an intersectional group of stakeholders — those in power along with minoritized groups — to deconstruct social stereotypes, understand intersectionality in practice, and get a more inclusive and pluralistic understanding of the human learning experience. This work requires developing data literacy not just so that students understand the data about them, but with a solid conception of justice that supports active engagement with the data (Knight et al., 2022). More concretely, new vistas on responsible LA would entail using specific tools to work with student data so its context can be considered and the silences in datasets identified. Ultimately, responsibility in LA would translate into promoting inclusion and diversity in LA data science practises and participatory design projects as a social site for mutual learning and co-liberation.

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[2] https://d4bl.org/
[3] https://alltechishuman.org/
[4] https://www.gida-global.org/

### Implication 2: Whose learning is addressed in LA data science practises?

Questions seeking to find out the groups that learner systems like ADM target, either implicitly or explicitly, or whose data counts in datasets, are motivated by the imperative to "look first at those at the margins" in an attempt to work "towards equity and inclusion" (D'Ignazio & Klein, 2020, p. 95, citing Dye et al., 2018). In this sense, there is still work to be done in LA regarding developing and using ADM systems for education. For instance, Brown (2020) explains that

> *Schools, colleges, and universities turn to virtual proctoring because they want to prevent cheating and increase the efficiency of exam proctoring. But disabled people have long confronted accusations of cheating, lying, or faking — especially about our disabilities. We've also often faced significant barriers to accessing digital technologies and remain disproportionately affected by the digital divide. It's no wonder we are deeply concerned about increasing surveillance, invasions of privacy, and discriminatory discipline arising from expanded use of automated proctoring. (p. 1)*

Hsu et al. (2021), examining student perceptions regarding an automated short-answer grader (ASAG) used for student homework and exam credit in a college-level computer science course, found that students benefitted (or were harmed) differently using systems like ASAG. A few respondents reported that groups with previous experience with ASAG systems and groups with prior experience in computer science (15%) might benefit unfairly. More importantly, 50% of respondents were concerned about groups of students "that could be at an unfair (dis)advantage for code reading questions"; 25.3% of respondents were concerned about "non-native speakers [who] could be worse at constructing answers in English or finding the right language to cater to the autograder" (Hsu et al. 2021, p. 10).

These examples tie back to issues of equity in LA (Holstein & Doroudi, 2022; Wise et al., 2021; Williamson & Kizilcec, 2022) that compel us to question what is known about the equitable access and use of novel technologies like ADM systems by minoritized groups of students? Reich and Ito (2017) remind us that often good intentions to deploy novel technologies in equitable ways fall short because of the quite different sociocultural and economic realities of those developing and deploying technology and those to be served; for instance, low-income and minoritized groups. Tressie McMillan Cottom's (2016) concept of "roaming autodidacts" paints technologists as most often imagining the average student as "a self-motivated, able learner that is simultaneously embedded in technocratic futures and disembodied from place, culture, history, and markets" (p. 214). Reich and Ito (2017) expand on this idea, saying that "Even when efforts are deployed with the explicit intention of serving disadvantaged youth, learners who are part of more entitled, tech-savvy, and highly educated families take advantage of new programs and opportunities more aggressively, and at higher rates. […] When learners encounter these biases, exclusion occurs in unintended but powerful ways" (pp. 9–10), meaning that feeling like an outsider can negatively impact student performance.

Such examples and research developments motivate us to understand better how different groups of students use systems like ADM. They also entice us to question the uneven effect of assessment on groups that can be disadvantaged and the efforts to address bias in technical terms (e.g., in the coding) rather than socio-technical terms (e.g., aiming to dismantle the matrix of dominance).

New vistas for responsible LA would look first at those at the margins of the education system and put equity at the centre of LA data science practises. Such aims could — beyond reducing social distance between developers, researchers, and the groups of students the design intends to serve — be instrumental in facilitating a better understanding of the specific needs at the margins of the education system and collecting data that matter for them, their identities, and their communities. D'Ignazio and Klein (2020) provide the example of the Westside Atlanta Land Trust (WALT[5]), which works for community empowerment centred around affordable housing in the city of Atlanta, Georgia, USA (Meng et al., 2019). Reflecting on the differences between working with data for social good and working with co-liberating data practices, D'Ignazio and Klein (2020) suggest that "data collection and participatory analysis become a gathering technology, a kind of campfire" (p. 145). The "campfire data model" differs from other participatory models that operate with an attitude to do "social good" by amplifying the asymmetric power relationships among social groups. Instead, the campfire model intends to bring together developers, researchers, and students from different sociocultural and economic backgrounds to work with data collection, analysis, interpretation, and communication to "build community, solidarity and shared understanding around a civic issue" (p. 145). The campfire model seeks to develop awareness and sensitize those involved about differences and inequity while enhancing social cohesion. It also has the effect of challenging the deficit narratives often associated with underserved

[5] https://www.carldisalvo.com/portfolio/walt

ISSN 1929-7750 (online). 

communities (p. 145). Working with such a model in LA could also be a strategy to work responsibly toward critical and decolonizing pedagogies.

**Implication 3: Whose ethics are mobilized in LA data science practises?**

A closer look at the ethical guidelines, principles, and codes of practice circulating in the LA community points at the prevalent use of Western ethical traditions and, more specifically, the core philosophical frameworks of virtue ethics, deontology, and utilitarianism. Such a development is not unique to LA. In the area of digital media, Ess (2020) underscores that over a decade ago, it was a small group of professionals in Western countries — mainly computer scientists and a few philosophers — who were concerned about "computer ethics," a term that manifested in the first professional code of computer ethics of the Association for Computing Machinery (ACM) in 1973, revised in 2018 (Ess, 2020, p. 216). However, we now have ethical frameworks from other philosophical stances and geographies. Ethics of care (Noddings, 2012; Tronto, 1998), Confucian ethics (Wong, 2012), intercultural computing ethics (Ess, 2020), and African perspectives (Capurro, 2008) are alternative developments providing principles, values, and modes of thinking and feeling focused on relational human beings, rather than rational individuals. Despite these broader ethical frameworks, the ethics of ADM systems are often addressed via the principles of fairness and bias (European Commission, 2022). No wonder issues of "lack of justice (West et al., 2016), inequality (Lawson et al., 2016; Roberts et al., 2016), unclear definition of harm (Willis et al., 2016), power embedded in LA systems (Scott & Nichols, 2017), profiling (West et al., 2016), moral discomfort (Jones, 2019a), ethical dissonance, and lack of intellectual freedom (Jones, 2019b)" are difficult to address in practice via current ethical frameworks and guidelines (Cerratto Pargman & McGrath, 2021, p. 12).

In fact, "Doing ethics involves much more than a kind of rule-book approach — i.e., picking a set of principles, values, etc., and applying these in a largely deductive, algorithmic manner to a problem at hand" (Ess, 2020, p. 218). Thus, in ADM, "doing ethics" in LA from a data feminist perspective would also entail acknowledging and challenging structural oppression reflected in data science practices.

Differences in understanding the root of the problem of fairness and bias in ADM systems have also been discussed by Green (2022), who situates algorithmic unfairness not in flawed people or flawed computer systems but in a flawed *methodology*. Formal algorithmic fairness "relies on a narrow frame of analysis restricted to specific decision points, in isolation from the context of those decisions" (Green, 2022, p. 4). It is aligned with "formal *equality* (which emphasizes equal treatment for individuals based on their attributes or behaviour at a particular decision point)"; in contrast, a more just understanding of algorithmic fairness will not address fairness as "a technical attribute of algorithms" but rather "on whether and how algorithms can promote *equity* in practice" (Green, 2022, p. 4). Green's (2022) distinction between equality (i.e., "*equal treatment* of every individual in an ahistorical context") and equity (i.e., "*Equitable treatment* means taking into account power differentials and distributing or redistributing resources accordingly") within decision-making processes is central in DF, which aims to design algorithms that are not only fair but also *socially just* (D'Ignazio & Klein, 2020, p. 62; Costanza-Chock, 2020). In this context, developing and deploying ADM systems in socially responsible ways would entail not only highlighting the practitioner's need to work with ethics in practice (Kitto & Knight, 2019; Figueras et al., 2022) but also the concept of equity (Prinsloo et al., 2022). Working with fairness and bias in LA with a focus on equity would imply applying the DF principle of reflexivity in LA *data science methods*. While accounting for reflexivity in research is a well-known methodological choice in fields like science and technology (Haraway, 1988), reflecting on the positionality of researchers, developers, or practitioners is not as common in LA; however, there is increasing acknowledgment of these politics, pedagogies, and practices in the LA community (Al-Mahmood, 2020; Buckingham Shum & Luckin, 2019). In this vein, considering reflexivity in the collection, classification, analysis, interpretation, and communication of LA data bound to ADM systems might contribute to discussing equity in the community; by doing so, we may be able to "develop an ability to reflect and take responsibility for one's position within the multiple, intersecting dimensions of the matrix of domination" (D'Ignazio & Klein, 2020, p. 64).

In summary, doing ethics in LA from a responsible stance would imply generating and adopting new methods, design strategies, tactics, and concepts to consider and address equity in LA data science practises. Such critical work will entail revising what and how data science programs for LA are taught. It will also invite the community to broaden its horizons for ethical discussions by engaging with a variety of ethical frameworks and perspectives, particularly feminism and relational ethics.

## 5. Conclusion

This paper examined the seven principles offered by DF to generate a battery of questions and three main implications for further developing and enabling a responsible stance in LA research and practice. This paper suggests that for a responsible perspective to develop in LA, a series of assumptions regarding power, equity, and representation issues in learning analytics must be unpacked. In this sense, we have argued for the following:

**Considering and challenging power** by 1) bringing together an intersectional group of stakeholders — those in power along with minoritized groups — to deconstruct social stereotypes, understand intersectionality in practice, and get a more holistic and pluralistic understanding of the human learning experience; 2) using specific tools to work with student data so its context can be considered and the silences in datasets identified; and 3) promoting inclusion and diversity in LA data science practises to make participatory design projects a social terrain for mutual learning and co-liberation.

**Looking first at those at the margins of the education system** and putting equity at the centre of the LA data science practises by 1) exploring the use of the "campfire model" to develop awareness and sensitize those involved about differences and inequity while enhancing social cohesion; 2) challenging the deficit narratives often associated with underserved communities; and 3) considering decolonizing LA pedagogies.

**Doing ethics** by 1) generating and adopting new methods, design strategies, tactics, and concepts to consider and address equity in LA data science practises; 2) revising what and how data science programs for learning analytics are taught; and 3) broadening the horizons of ethical discussions by engaging with various ethical frameworks and perspectives, particularly feminism and relational ethics.

## Declaration of Conflicting Interest

All review processes and editorial decisions at all stages of the manuscript submission have been made independent of, and blinded from, Knight and Viberg — who were, respectively, outgoing and incoming co-editors-in-chief of this journal. The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

## Funding

The publication of this article received financial support from the Wallenberg AI, Autonomous Systems and Software Program — Humanities and Society (WASP-HS), Grant MMW 2020-0138.

## Acknowledgments

The authors would like to thank Rebecca Ferguson from The Open University, and Kirsty Kitto from University of Technology Sydney, for engaging discussions on responsible learning analytics and acknowledge their inspiring comments on an early draft of this manuscript.

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