Mapping *responsible* learning analytics: a critical proposal

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Abstract
This chapter examines the notion of responsible learning analytics. Such an approach requires institutions to take an answerable and response-*able* approach to using student data. Learning analytics, like all educational technology, is shaped by a range of social, political, economic and cultural agendas. As such, this chapter argues that ethical and responsible learning analytics is central to a consideration of each of the eight dimensions of Khan's e-learning framework (Khan, 2010). The chapter concludes by suggesting a number of pointers for higher education institutions to ensure the adoption of a responsible and responsive approach to learning analytics.

Introduction
Any discussion on the potential and risks of data analytics in education is entangled in the wider debates and discourses about the "data revolution" (Kitchin, 2014); concerns around often obscurbe and intersecting surveillance mechanisms and structures (Pasquale, 2015; Solove, 2001); the increasing role of algorithmic decision-making and machine learning (Jandrić, Knox, Macleod, & Sinclair, 2017); predictive learning analytics (Ekowo & Palmer, 2017); and the public and policy imaginaries regarding uses of data in education (e.g., Prinsloo, 2017a; Williamson, 2017).

Against this backdrop, the notion of '*responsible* learning analytics' is implicit as a research focus and field of praxis, albeit not as a dominant theme (Prinsloo & Slade, 2017a). An overview of the social imaginary relating to learning analytics covers a range of topics, for example, claims of the huge potential of the collection, analysis and use of student data and emerging evidence of its use in a range of higher education contexts (Clow, 2013; Peña-Ayala, 2017; Siemens, 2013). Much of the published research on learning analytics focuses on increasing the efficiency of learning and providing faculty, institutions and students with often real-time feedback in order to make (more) informed and more responsible choices (Buckingham Shum, 2012; Prinsloo & Slade, 2017a; Roberts, Chang, & Gibson, 2017).

Higher education has routinely collected, analysed and used student data for a number of purposes, such as marketing, enrolment planning, instructional design and student support, operational resource allocation and regulatory reporting. However, the recent rapid growth of access to increasing volumes, variety and velocity of data necessitates a critical interrogation of what the notion of *responsible* learning analytics might look like. And given the speed of technological development, any such consideration should take cognisance of the broader discourses around Big Data, Artificial Intelligence (AI), algorithmic decision-making and advances in software and tools for analyses, and how these all shape learning analytics research and practice (Bienkowski, Feng, & Means, 2012; Prinsloo, 2017a; Prinsloo, Archer, Barnes, Chetty, & Van Zyl, 2015).

In the noisy scholarly, public and increasingly commercial spheres of claims and counter-claims relating to learning analytics applications, we should not forget that learning analytics is primarily about *students* and *their* learning (Gašević, Dawson, & Siemens, 2015). There is growing interest in issues such as the scope of student privacy, the scope and obligation of institutions to respond ethically, and the need to move towards *student-centred* learning analytics (Pardo & Siemens, 2014; Slade, 2016; Slade & Prinsloo, 2013; Prinsloo & Slade, 2017a; Willis, Slade & Prinsloo, 2016). However, the range of ethical considerations around learning analytics and increasingly, the moral fiduciary obligation arising from our collection and analysis of student data – are often uncomfortable reminders of unchartered fields of scholarly reflection and empirical research (Bailey, & Sclater, 2015; Prinsloo & Slade, 2016; Roberts, Chang, & Gibson, 2017).

An etymology of the word 'responsible' suggests not only the need to be *answerable* and *accountable*, but also to being *response-able* and having an *obligation to act* (Prinsloo & Slade, 2014a). In this chapter we propose that an answerable and response-*able* approach to learning analytics cuts across the whole spectrum of higher education's approach to teaching and learning, that of "planning, designing, evaluating and implementing [online] learning environments where learning is actively fostered and supported" (Khan, 2010, p. 44). We consider the notions of 'accountability', 'transparency' and 'response-ability' based on the fiduciary duty of higher education, and the reality and impacts of the asymmetrical power relationships between higher education and students (Slade & Prinsloo, 2013).

The notions of 'responsible' and 'response-able' learning analytics apply to all three levels of learning analytics as proposed by Buckingham Shum (2012) namely micro (individual user actions), meso (institution-wide application and use) and macro level (region/state/ national/international). The micro-level use of learning analytics is of "primary interest to learners themselves, and those responsible for their success, since it can provide the finest level of detail, ideally as rapidly as possible" (Buckingham Shum, p. 3). Meso-level learning analytics refers to learning analytics used together with business intelligence to constitute "academic analytics" (Buckingham Shum, 2012, p. 3). Macro-level learning analytics "seek to enable cross-institutional analytics" (Buckingham Shum, 2012, p. 3) used in, for example, surveys of current institutional practices or improving inter-institutional state-wide data. [See Khalil, Prinsloo and Slade (2018) for an exploration of the ethical dimensions in each of these three different levels of learning analytics]. While acknowledging that all three levels of learning analytics require a responsible approach, this chapter specifically focuses on the micro and meso levels of learning analytics.

In this chapter, we propose that the notion of responsible learning analytics has implications for *each* of the eight dimensions of Khan's e-learning framework (Khan, 2010) as opposed to the 'ethical' dimension alone. While we accept that the quality of data (as proposed by Stiles, 2012) is an important consideration in the ethical collection, analysis and use of student data, responsible learning analytics entails much more than ensuring data privacy, guarding against faulty analysis or interpretation or responding to unexpected consequences. Conceptualising and institutionalising the notion of *responsible* learning analytics has implications for each dimension of Khan's (2010) framework – institutional, pedagogical, technological, interface design, evaluation, management, resource support and ethical.

What makes a proposal critical?

This chapter aims to address the notion of responsible learning analytics as a critical issue, worthy of consideration. We also take a specific *critical* stance, emphasizing the different dynamics and asymmetries in power relations between students, institutions and other stakeholders. In following Selwyn (2014) we view learning analytics, like all (educational) technology, "as a knot of social, political, economic and cultural agendas that is riddled with complications, contradictions and conflicts" (p. 6). The ways in which student data are defined, collected, analysed and used are integral parts of "the complex ways that social, economic and political tensions are 'mediated' in educational settings" (Selwyn, 2014, p. 4). Without discounting the huge potential of learning analytics to contribute to our understanding of the complexities in student success and retention, we should also guard against a certain "techno-romanticism" and claims of "truthiness" (Selwyn, 2014, p. 10) formulated in the Global North or in the corridors of venture capitalism or Silicon Valley (Selwyn, 2014; Watters, 2015). In this respect we regard a dose of scepticism as not only in order, but also necessary. We see data (and its collection, analysis and use) as inherently framed in technical, economic, ethical, temporal, spatial and philosophical ways (Kitchin, 2014).

We should also acknowledge a deeper rationale in our adoption of a 'critical' stance, namely the broader tenets of critical theory. Critical theory is multi-faceted with many different emphases (Sim and Van Loon, 2004), and its scope, authors and main aims have been contested, discredited and at times severely criticised (Poster, 1989; Sim & Van Loon, 2004). Central to a critical approach would be to "to think through the relationship between culture, forms of domination, and society" (Apple, 2004, p.182). According to Horkheimer, '…a theory is critical only if it meets three criteria: it must be explanatory, practical, and normative, all at the same time. That is, it must explain what is wrong with current social reality, identify actors to change it, and provide clear norms for criticism and practical goals for the future' (Bohman, 1996, p. 190). A critical approach takes the side of individuals and groups whose agency and choices are impacted upon by those in power (Burbules & Berk, 1999). If we consider analytics as foundational in making 'truth' claims and determining what is valued, it is crucial then to note that learning analytics as epistemological enterprise analysing truth and knowledge claims and exposing falsehood. A critical approach secondly is also concerned with asking "who benefits and on what basis?"

In exploring a critical approach to what 'responsible learning analytics' might mean, we suggest that learning analytics be seen as "a structuring device, [that is] not neutral, informed by current beliefs about what counts as knowledge and learning, coloured by assumptions about gender/race/class/capital/literacy and in service of and perpetuating existing or new power relations" (Prinsloo & Slade, 2017d).

Mapping the contours of responsible learning analytics

Considering data analysis as an “art” (Ibrahim, 2015) and even perhaps as a “black art” (Floridi, 2012), creates the impression of data analysis as giving access to ‘hidden’ knowledge. Such insights would not normally be accessible to the uninitiated or to those without a statistical or programming background, and any real understanding of the data might only be accessed through an *interlocutor*. Institutional researchers largely fulfil the role of interlocutors by translating data into information and knowledge to institutions, support staff and students. It is therefore relevant to suggest that “with power comes responsibility and *accountability*” (Prinsloo & Slade, 2017d; emphasis added).

The notion of being ‘responsible’ calls forth a number of possible meanings, for example, to:

- Be answerable/accountable/liable when things go wrong;
- Be blameworthy – by not keeping promises, not fulfilling contractual obligations, not adhering to legal and regulatory frameworks;
- Act ethically and morally;
- Be response-able - to have an ability to respond to identified needs/gaps;
- Have an obligation/contractual duty to act;
- Fulfil a fiduciary duty to act;
- Be transparent about criteria and processes.

Within this range of possible interpretations, it is clear that being responsible is fundamentally *relational.* There is an implied responsibility *for* a task or a person, with an associated accountability to the object of that responsibility or to some oversight structure, mechanism or individual(s). Given the nature of learning analytics, there is a danger that it becomes abstracted into spreadsheets and dashboards. Once abstracted, it becomes easy to forget the impact of the stakeholders involved. That is, the identity and role of those collecting the data (their assumptions, biases, expertise, race, gender, etc.), the values, assumptions and understanding of data of the institution commissioning the collection, analysis and use of data, and finally, those from whom we collect data. Once processed, it is also easy to overlook that the data that we collect are incomplete and fluid.

A basic point of departure for defining a responsible approach to learning analytics begins with an adherence to legal and regulatory frameworks and policies. However, responsible learning analytics should go beyond mere adherence and move towards learning analytics as *moral* practice. This assumes embracing a teleological approach to learning analytics, which expands the scope of responsibility found in a deontological approach. Whereas a deontological approach is rule-based and appropriate in stable environments, a teleological approach emphasises the “potential for harm, individuals’ agency in making informed, nuanced decisions regarding the collection, analysis and use of their data and recourse to action in cases of harm or breach of privacy” (Prinsloo & Slade, 2017d). [Also, see Velasquez, Andre, Shanks, & Meyer, 2015].

Responsibility typically begins at registration when students and institution enter into an agreement that has not only *legal* standing but also signifies a social or fiduciary contract between the institution and students (e.g. Bailey, & Sclater, 2015).

The responsibility arising from the contractual nature of learning contract

The legal underpinnings of responsible learning analytics imply not only the obligation to protect students' privacy and to ensure the ethical governance of the storage and access to the data, but also to use the data for the purpose for which it was originally collected (Slade & Prinsloo, 2013). The learning contract between the institution and students implies a fiduciary duty to act and ensure efficient and appropriate learning experiences. This not only implies the provision of lectures, learning materials and appropriate support, but also a duty to act to ensure the well-being of students in the context of the scope of the contract (Prinsloo & Slade, 2017c). The legal duty of institutions includes preventing discrimination and bullying, providing equitable access for disabled students, and responding to students' psychological needs pertaining to their learning journeys (see Prinsloo & Slade, 2017c).

While we recognise that students also have a responsibility to fulfil their part of the learning contract, the institution, as provider of the services, has a special duty with regard to students' data and their use. There is a danger that learning analytics focuses on what students do or don't do, and "fails to examine *institution*-related behaviors and *institution*-related characteristics such as the climate of academia" (Godor, 2016, p. 2). It falls outside the scope of this article to discuss the full contractual duty that arises from the learning contract. [See Prinsloo & Slade (2017c) for an exploration of the legal obligations to act in the context of learning analytics]. Suffice to suggest that though common law does not enforce a duty to rescue, it does not erase an implicit moral duty to act from an ethical perspective (Prinsloo & Slade, 2017c).

The social contract between institution and students: implications

The nature of the social contract between organisations and individuals has irrevocably changed (e.g. Bauman & Lyon, 2013; Henman, 2004; Mayer-Schönberger & Cukier, 2013). In a learning analytics context, there is an assumption that the collection, analysis and application of student data are done in the best interests of the student. Indeed, given the additional insight that learning analytics offers, we might suggest that the social contract between HEI and student presents an obligation to act on what is known (or predicted) (Prinsloo & Slade, 2017c). It is fair to say though that the idea of a social contract obscures many of the current realities of the relationship between student and institution.

Although learning analytics offers enormous potential in providing both insight and the additional means to directly support and signpost student learning, there is not always complete recognition that this takes place in the context of unequal power. Students are often unaware of the range of learning analytics activity relating to their own data and there may be few opportunities for students to opt out of being included. It is not unusual for both institution and student to see students as merely as the producers of data and passive recipients of services rather than agents in their own learning (Diaz & Brown, 2012; Prinsloo & Slade, 2014b; Stoddart, 2012). "The question of whose interests are served is central. And of course, there is clear advantage for those who collect and control the data and information over those who provide the data and seek to benefit from that contribution" (First Nations Information Governance Centre, 2016). [See Prinsloo, 2017b].

Response-able: mapping our obligation to act

The second aspect worthy of consideration is the need to be response-able and responsive. Being able to respond does not necessarily imply responsiveness, and being responsive does not always mean that the institution and its faculty and student support staff have access to the necessary resources to respond appropriately and effectively. In a recent paper, Prinsloo and Slade (2017c) explore the moral duty that arises from the learning contract between institutions and students and map several factors that impact on the institution's ability to respond and its responsiveness, such as (1) a lack of understanding or a theory/practice divide; (2) the role of political will and institutional responsiveness; (3) a lack of integration in institutional sense-making; (4) finance-driven resource constraints; and (5) student responsibility and autonomy.

Responding to what we know and/or may understand is increasingly dependent on having the necessary resources to respond (Prinsloo & Slade, 2014a). In the context of increasing costs and funding constraints, many higher education institutions are taking a triage approach in choosing how they allocate resources. As Prinsloo and Slade (2014a) indicate, this can lead to a focus on students who are more likely to provide a longer term return as a result of interventions. This combination of funding constraints with an increasing need to support often underprepared students places institutions in a moral and legal double-bind – even if they want to provide the support that students need, they simply cannot.

Responsiveness implies not only having the resources and capacity to respond to an identified need, but actually using those resources to intervene or support. Unutilised reports and analyses are germane to higher education, whether at institutional or student-levels. At an institutional level the impact of institutional research depends on whether "a problem is recognised as serious and requiring a new solution; when the policy community develops a financially and technically workable solution; *and when political leaders find it advantageous to approve it*" (El-Khawas, 2000:5; emphasis added). At a student level, there are concerns that reductionist and quantification approaches in learning analytics do not sufficiently allow for the complexities of students' learning (Macfadyen & Dawson, 2012). The effectiveness of the use of dashboards to inform student choices and agency is also still unclear (Gašević, Dawson, & Siemens, 2015; Verbert, Govaerts, Duval, Santos, Van Assche, Parra, & Klerkx, 2014).

The Khan (2010) framework through a responsible and response-able lens

Foundational to a critical approach in considering the Khan (2010) framework through a responsible and response-able lens is the claim that "the Web has become a powerful, global, interactive, dynamic, economic and democratic medium of learning and teaching at a distance" (Khan, 2010, p. 42). Few would contest that the Web is immensely powerful and not only perpetuates particular understandings of economic well-being, but also impacts on the economic potential and well-being of millions of individuals who are excluded from the benefits of the Web. We do not dispute the immense potential and affordances of online education, but there is ample evidence that suggests that online education might perpetuate rather than decrease inequalities (Bonk, Lee, Reeves & Reynolds, 2015; Rohs & Ganz, 2015; World Bank, 2016).

A recent report by the World Bank (2016) states that “Digital technologies have spread rapidly in much of the world. Digital dividends—the broader development benefits from using these technologies—have lagged behind” (p. 2). More than 60% of the world’s population is still offline, and “some of the perceived benefits of digital technologies are offset by emerging risks” such as “polarised labour markets and rising inequality” with technology “replacing routine jobs, forcing many workers to compete for low-paying jobs” (p. 3). The report also provides evidence that “the better educated, well connected, and more capable have received most of the benefits—circumscribing the gains from the digital revolution” (p. 3). While evidence suggests that access to the Web is increasing, access and use are still, in many contexts, influenced by geopolitical location and regulation, gender and culture (Pew Research Global, 2016). We have to consider evidence that with the growing access to

> the Internet and to wireless communication, abysmal inequality in broadband access and educational gaps in the ability to operate a digital culture tend to reproduce and amplify the class, race, age, and gender structures of social domination between countries and within countries. (Castells, 2009, p. 57)

Networks then not only include but also exclude, and “the cost of exclusion from networks increases faster than the benefits of inclusion in the networks” (Castells, 2009, p. 42).

A second important consideration is to acknowledge the impact of context – whether micro (student), meso (institutional) or macro (social, political, economic, technological, environmental and legal) (Buckingham Shum, 2012; Subotzky & Prinsloo, 2011). We are “condemned to context” (Tessmer & Richey, 1997, p. 88) and cannot ignore the variety of factors indigenous to a particular context. We therefore agree with Jonassen’s proposal that “[c]ontext is everything” (Jonassen, 1993, in Tessmer & Richey, 1997, p. 86).

With the above in mind, ethics in online learning is not a separate element among the eight other dimensions as proposed by Khan (2010), but rather encompasses the other seven dimensions (Figure 1). One of the reasons why this is so important, is the general belief that adding a policy on ethical data collection and analysis will address the many concerns, or having an ethical review process and structure will be a solution. As Willis, Slade and Prinsloo (2016) suggest, the collection, analysis and use of student data are embedded in and dependent on a variety of processes with different owners and oversight. We should therefore consider the ethical implications of learning analytics in each of the seven remaining dimensions of Khan’s (2010) e-learning framework.

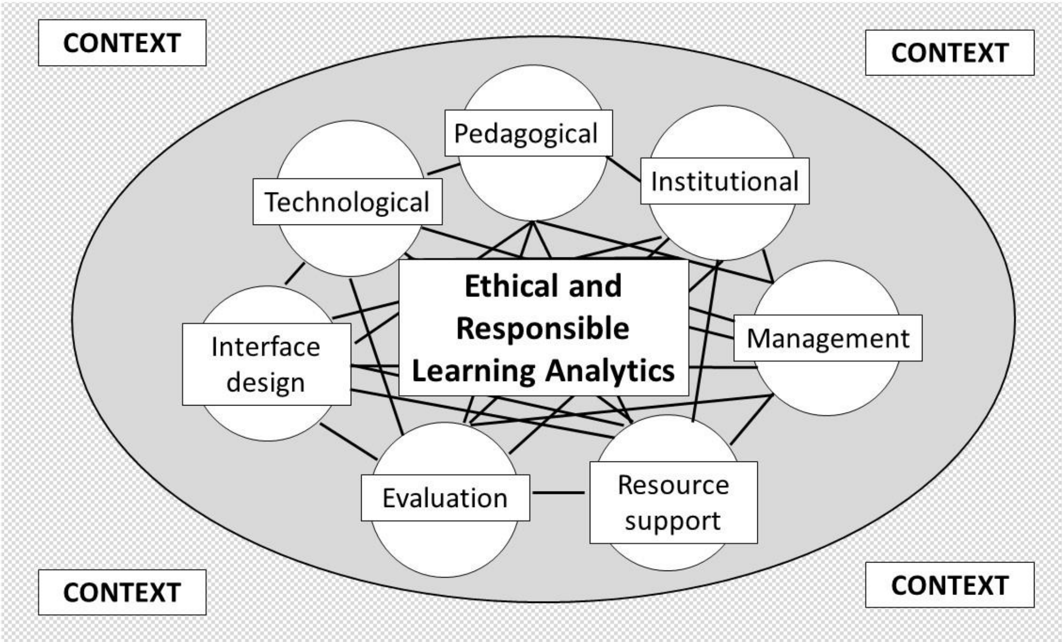

Figure 1: Towards responsible and response-able learning analytics

Figure 1 illustrates ethical and responsible/response-able learning analytics as *central* in considering the collection, analysis and use of student data in micro, meso and macro contexts. In the next section we will illustrate the ethical aspects in each of the dimensions and show how an ethical lens impacts on higher education's responsibility and responsiveness.

A critical proposal

This section details some of the ethical aspects in the other seven dimensions of e-learning (Khan, 2010) that impacts on a responsible and responsive collection, analysis and use of student data.

Institutional

As Khan (2010) suggests, the institutional dimension includes administrative and academic affairs as well as student services. In the context of learning analytics, it is clear that the institutional dimension will include ensuring an ethical and responsible policy and regulatory environment, the necessary hardware and software, human resources, infrastructure and ensuring an integrated responsive environment. In the light of the asymmetrical power-relationship between the institution and students, and the institution's fiduciary duty, it is clear that the institutional dimension to responsive and responsible learning analytics is crucial.

Management

This dimension refers to the maintenance of the learning environment and the distribution of information and as such, impacts directly on learning analytics. While student data are often stored in disparate data bases and used by a variety of stakeholders for a variety of purposes, the basis for most learning analytics is the learning management system (LMS). As institutions increasingly move online and the amount, variety and velocity of available on and outside of the LMS increase, it will be *irresponsible* of institutions not to collect, analyse and use this data to improve students' chances of success. For the data on the LMS to become information relies on not only on technological capacity (see the next point), but increasingly on ensuring that individuals have the necessary understanding of the limitations, assumptions, biases, and incompleteness of the data and of our understanding of the complexities of student success.

Technological

There is evidence that many institutions do not fully appreciate the sheer amount of data that can be found on the LMS nor how, if combined with other data sources/banks, it *may* provide a more complete picture of students' learning, However, it is one thing to have access to data, and another thing to *intentionally* collect, analyse and use the data. The latter requires not only technological capacity and infrastructure, but also the technological capability to disseminate information, primarily to students but also to faculty and support departments.

Pedagogical

Amid the hype surrounding learning analytics and the increasing volume, variety and velocity of student data, it is easy to forget that the primary goal of learning analytics is to inform and increase the effectiveness of *learning* (Gašević, Dawson, & Siemens, 2015). There are also concerns about the relative scantiness of evidence that learning analytics has actually improved student outcomes. Despite these concerns, the basis for responsible learning analytics is driven by a wish to understand patterns in individual student and cohort data, and to inform pedagogical strategies such as formative assessment, cognitive load, etc. Linked to this though is the follow-through - to ensure that we are able to respond to whatever the analyses point out. As Prinsloo and Slade (2015) point out, 'knowing' that specific students are at risk of failing or need additional support brings with it additional responsibility. In an increasingly resource-constrained higher education sector, we therefore need to have both the political will and resources to use student data responsibly and in responsive ways.

Central to the pedagogical dimension of responsible learning analytics is being student-centred. While learning analytics often focuses on what data are available and what institutions can do with that data, responsible learning analytics also considers what data *students* need to make better informed decisions, i.e., what data and analyses do institutions have access to that will allow students to make informed decisions about their own learning trajectories.

Interface design

Khan (2010) includes a range of issues in this dimension such as "page and site design, content design, navigation, accessibility and usability testing." As stated earlier, given that a large proportion of learning is facilitated through and on the LMS, the ways and frequency with which students engage with study pages on an LMS offer significant potential to understand the impact of pedagogical strategies and how they must be best visualized and structured on the LMS. To not make use of user data to improve study design seems irresponsible and contradictory to the institution's fiduciary duty. Having said that, there is a need to take care in making broad assumptions around issues such as student click rates. Such measures can be used as proxies for engagement and learning and there is much to understand regarding the inferences that can safely be drawn. There is a temptation to suggest correlation and/or causation between user patterns and engagement with, inter alia, student success. User data may provide us with data regarding usability and interface design, but it may be irresponsible to make further claims regarding correlations between user experience and student success or student risk.

Resource support

There is a danger that many learning analytics models or approaches to research fall into a deficit model of thinking where the emphasis is placed on what students lack or need in order to 'fit', and that this in turn informs our selection of data sources, our designs and our analyses. If this dimension entails fostering "meaningful learning", then there is a need for faculty and the institution to ensure that there are sufficient resources to respond effectively and appropriately to identified needs and gaps. This dimension speaks specifically to the second aspect of an ethical approach to responsible learning analytics, namely to be response-able.

A central issue often neglected in considering this dimension of responsible learning analytics is the consideration of students as resourceful and as being agentic. While we acknowledge that many elements impacting on learning fall outside the locus of control of students (and often, outside the locus of control of the institution), we should not underestimate students' agency and choice. As indicated under the 'pedagogical' dimension above, student centred learning analytics proceeds from the basis that students are not data-providers or data-points, but that they are and should be involved in determining what data would be valuable for them to make better informed decisions within their loci of control.

Evaluation

It may not be an overstatement to suggest that published research in learning analytics tends to focus on how learning analytics has assisted and informed learners, with less emphasis on the evaluation of instruction and the learning environment as suggested by Khan (2010). Much of the research published shares findings on what students *'do'* (or don't do), and how data are used to determine their potential to fail, their need for additional support/intervention, and their responsiveness to interventions. With regard to the use of Artificial Intelligence (AI) and machine learning in the learning analytics space, students' actions or non-actions will increasingly shape learners' experiences often without them realizing it, or having access to the criteria and reasoning embedded in the algorithms. There are increasing concerns around how AI can amplify and naturalize longstanding biases "rendering them more opaque to oversight and scrutiny" (Selbst & Barocas, 2017, p. 4).

A further implication of taking an ethical approach to responsible and responsive learning analytics is to point to the current hiatus in the discourses in learning analytics, namely to *also* consider the evaluation of instruction and the learning environment. We have already stated that much of the thinking in learning analytics discourses is based on a deficit model. As Subotzky and Prinsloo (2011) indicate, such an approach impoverishes our understanding of the complexities of student success as the result of a multiplicity of factors, often interdependent and mutually constitutive. Considering student learning as taking place and facilitated in the nexus between students, the institution and the macro societal context (political, economic, social, technological, legal and environmental), the singular focus in learning analytics on what students do or don't do is rather unfortunate. In terms of the Khan (2010) proposal that evaluation in the context of e-learning includes also the evaluation of the instruction and the learning environment, responsible learning analytics should seek to understand students' action or inaction in context.

(In)conclusions and next steps

Higher education is not immune to broader societal changes and should consider seriously the potential, risks and challenges in the collection, analysis and use of student data. The 'digital revolution' and learning analytics, per se, are not benign phenomena and can perpetuate historical exclusions and biases and/or normalise incomplete and often deficient and erroneous understandings of student learning.

In the light of the contractual and fiduciary duty of higher education, as well as the asymmetrical power relations between the institution and students, it is clear that we need to guard against a certain "techno-romanticism" and claims of "truthiness" (Selwyn, 2014, p. 10) and not forget that with power comes responsibility. Higher education has access to a greater variety of data from a range of disparate sources, and with greater technological capability to collect and analyse this data, than ever before. With this increased access and capabilities, we should consider our legal and moral responsibilities and our ability to respond, appropriately and effectively to identified risks and support needs.

In order to ensure a responsible and responsive approach to learning analytics, higher education institutions might usefully consider the following pointers:

- As a first step, institutions might consider current practices for data collection, analysis and use. For example, what data are already collected and by whom, who has access, under what conditions and for what purposes? A mapping of an institution's data landscape should serve as a basis for determining the extent to which the institution fulfils its *legal* obligations.
- Although regulatory and legal frameworks tend to lag technological developments, and despite a recognition that ethical policies and frameworks are by themselves largely ineffective, there remains a need for institutions to be held to account. As Brin (2016) states: "Ethics are the mirror in which we evaluate ourselves and hold ourselves accountable" (par. 39) and that holding actors and humans accountable still works "better than every single other system ever tried" (par.42). Institutions cannot afford *not* to have a policy framework that explains the institution's beliefs and approaches to the collection, analysis and use of student data. Though the formulation of such a policy seems to be straightforward, Willis, Slade and Prinsloo (2016) point to the complexities in ensuring an ethical approach in learning analytics.
- After ensuring compliance with relevant legal frameworks, institutions should consider the moral obligations of 'knowing'. What do we already 'know' about students' needs and risks and how do we respond to these needs and risks? What do students need to know in order to make more informed decisions about their own learning? What data do students have that might facilitate better and more appropriate learning and support opportunities? [See Prinsloo, 2017b].

In an increasingly resource-constrained world, higher education institutions will increasingly deal with the paradox of the legal and moral implications of knowing students' risks and learning needs, and the potential of *not* having the necessary resources to fulfil their contractual and fiduciary duties to students.

Ethics in learning analytics has moved from being a marginal issue to one of the central concerns in research around learning analytics (Prinsloo & Slade, 2017b). In this paper we have not only mapped the different nuances and applications of a responsible and responsive learning analytics, but also argued that the ethical dimension of online learning should both inform and form the basis for the other seven dimensions in Khan's (2010) framework.

The following questions may be considered in mapping the current nature and state of responsible and response-able learning analytics in institutions:

1. To what extent is an ethical and responsible approach to the collection, analysis and use of student data embedded *in all seven dimensions* of Khan's (2010) framework in a particular institution, or is it considered to be a separate issue?
2. Who bears the responsibility within the institution to ensure an ethical approach to the collection, analysis and use of student data?
3. How 'response-able' is the institution to findings flowing from the collection and analysis of student data? How can an institution ensure an effective and appropriate allocation of resources to assist students-at-risk or students who have specific learning needs?
4. How are the institution and individual users of student data held accountable for, inter alia, the appropriate and ethical collection, analysis and use of student data? To what extent are students involved in determining the scope and intended use and interpretation of their data?
5. What infrastructure, hardware and software, and human resources are needed to ensure the *effective*, *appropriate* and *responsible* collection, analysis and use of student data?

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