Here Be Dragons: Mapping Student Responsibility in Learning Analytics

Book Section

Chapter 7
Here Be Dragons:
Mapping Student Responsibility in Learning Analytics

Paul Prinsloo
Unisa, South Africa

Sharon Slade
The Open University, UK

ABSTRACT

Learning analytics is an emerging but rapidly growing field seen as offering unquestionable benefit to higher education institutions and students alike. Indeed, given its huge potential to transform the student experience, it could be argued that higher education has a duty to use learning analytics. In the flurry of excitement and eagerness to develop ever slicker predictive systems, few pause to consider whether the increasing use of student data also leads to increasing concerns. This chapter argues that the issue is not whether higher education should use student data, but under which conditions, for what purpose, for whose benefit, and in ways in which students may be actively involved. The authors explore issues including the constructs of general data and student data, and the scope for student responsibility in the collection, analysis and use of their data. An example of student engagement in practice reviews the policy created by the Open University in 2014. The chapter concludes with an exploration of general principles for a new deal on student data in learning analytics.

INTRODUCTION

It is easy to be seduced by the lure of our ever-increasing access to student data to address and mitigate against the myriad of challenges facing higher education institutions (HEIs) (Greenwood, Stopczynski, Sweat, Hardjono & Pentland, 2015; Stiles, 2012; Watters, 2013; Wishon & Rome, 2012). Challenges include, inter alia, changes in funding regimes and regulatory frameworks necessitating greater accountability to a widening range of stakeholders such as national governments, accreditation and quality assurance bodies, employers and students (Altbach, Reisberg, & Rumbley, 2009) (also see Bowen & Lack,

DOI: 10.4018/978-1-4666-9983-0.ch007

2013; Carr, 2012; Christensen, 2008; Hillman, Tandberg, & Fryar, 2015; New Media Consortium, 2015; Shirky, 2014). Though anything but a recent development (see e.g., Hartley, 1995), funding increasingly follows performance rather than preceding it (Hillman et al., 2015). The continuous decrease of public funding for higher education increases the pressures on higher education institutions to not only be accountable to an increasing number of stakeholders, but also to ensure the effectiveness of their teaching and student support strategies. There are also increasing concerns that HEIs have not solved, nor done enough to attempt to solve, the 'revolving door' syndrome whereby many students either fail to complete their courses or programmes or take much longer than planned (Subotzky & Prinsloo, 2011; Tait, 2015).

As teaching and learning increasingly move online and digital, the amount of digital data available for harvesting, analysis and use increases. HEIs' access to and use of student data is thought to have the potential to revolutionise learning (Van Rijmenam, 2013) with the expectation that it will change 'everything' (Wagner & Ice, 2012), that student data is the *new black* (Booth, 2012) and the *new oil* (Watters, 2013). The current emphasis on the 'potential' of learning analytics without (as of yet) definitive evidence that learning analytics does indeed provide appropriate and actionable evidence (Clow, 2013a, 2013b; Essa, 2013; Feldstein, 2013; Selwyn, 2014), can produce and sustain a number of 'blind spots' (Selwyn & Facer, 2013).

In a climate of expectation then that the increased collection and analysis of student data can provide much needed intelligence to both increase our understanding of the challenges and issues facing HEIs and may further assist in formulating more effective responses; there are also concerns that data1 and increasingly Big Data, is not an unqualified good (Boyd and Crawford, 2012, 2013; Kitchen, 2014a). The harvesting, analysis and use of student data must also be seriously considered amidst the discourses surrounding privacy, student surveillance, the nature of evidence in education, and so forth (Biesta, 2007, 2010; Eynon, 2013; Prinsloo & Slade, 2013; Selwyn & Facer, 2013; Wagner & Ice, 2012).

In much of the current discussions around learning analytics, the emphases are on the institution, the potential of data, modelling and algorithms and on students as producers of data, modelling and algorithms. Though student data is central in learning analytics, the role of students is mostly limited to the production of intelligence for more effective teaching and resource allocation. Students are seen as (merely) generators of data, objects of surveillance, customers and recipients of services (Kruse & Ponjasapan, 2012).

A further concern is a view that for most sites involving the use of personal data, the Terms and Conditions (TOC) of use are generally considered to be ineffective in providing users with informed control over their own data. More seriously though, many users simply do not take the time nor have the necessary technical or legal expertise to engage with those TOCs and make informed and rational decisions (Antón & Earp, 2004; Bellman, Johnson, & Lohse, 2001; Earp, Antón, Aiman-Smith, & Stufflebeam, 2005; Lane, Stodden, Bender, & Nissenbaum, 2014; Miyazaki & Ferenandes, 2000). Higher education is no exception to this dire state of affairs. Analyses of the Terms and Conditions (TOCs) for three major providers of Massive Open Online Courses (MOOCs) found that students' role in the data exchange is severely limited to the sole responsibility to ensuring that the information provided by them is correct and current (Prinsloo & Slade, 2015a). Once students accept such TOCs, they have very little control over what data is collected, used and shared; the persons or entities with whom their data is shared; the governance and storage of their data; and even access to their own digital profiles.

In the light of the asymmetrical power relationship between students and HEIs, where students have little choice but to accept the TOCs, there is a need to think differently with regard to the ethical issues in the collection, analysis and use of student data (Slade & Prinsloo, 2013). If one accepts that higher education is, amongst other things, a moral practice based on a social contract between students and their institutions, it is impossible to ignore the fiduciary duty of HEIs to re-think the student role in the value chain of data exchange.

The rationale for rethinking the role and responsibilities of students in this context is found in an awareness of the *ethical* implications and considerations in learning analytics. Although there are promising signs of increasing attention paid to issues surrounding privacy and ethics in learning analytics (Eynon, 2013; Pardo & Siemens, 2014; Siemens, 2013), the practical challenges associated with adopting institutional policy and frameworks to address those issues are complex (Prinsloo & Slade, 2013). It is believed that the Open University (UK) policy on the *Ethical use of student data* (Open University, 2014) is the first of its type within the context of higher education.

This chapter argues that ignoring the role of students in the context of the value exchange of their data is seriously underestimated and under-theorised. We propose that students' responsibility in the data exchange is much more than just ensuring that the information provided is correct and current. Students can and should actively collaborate in the institution's collection, analysis and use of that data. Students' agency is much more than just opting in or out of having data collected, analysed and used. We therefore position students as *agents* in a student-centric approach (e.g., Kruse & Pongsajapan, 2012; Slade & Prinsloo, 2013; Prinsloo & Slade, 2015a) to learning analytics.

In times past, ancient maps were used to record what was already known and to guide exploration into areas which were not yet familiar. Such maps were informed and shaped by the cartographers' skills, knowledge and understanding of the areas they were trying to map. Areas unknown to the cartographer were often accompanied with warnings, such as 'here be dragons.'

In the new world of learning analytics, this chapter attempts to map some of the current approaches to student data and more specifically the potential of student-centric learning analytics. The authors are aware that the simple binary of opting in or out is does not provide an effective nor sufficiently nuanced approach (Prinsloo & Slade, 2015a). In exploring and mapping the unknown areas of student responsibility in the context of learning analytics, it is perhaps pertinent to suggest that 'here be dragons.'

ENGAGING WITH DATA AS *CONSTRUCT*

Data in a variety of formats has always been essential to scientific research, commercial enterprises and higher education, but it is also fair to say that *[d]ata have traditionally been time-consuming and costly to generate, analyse and interpret, and generally provided static, often course, snapshots of phenomena* (Kitchen, 2014a, p. xv). The production and availability of data have overtaken our understanding of the complexities and ethical challenges of data as phenomenon (Barnes, 2013; Diakopoulos, 2014a; Eubanks, 2015; Koponen, 2015; Mehta, 2015). *While many analysts may accept data at face value, and treat them as if they are neutral, objective, and pre-analytics in nature, data are in fact framed technically, economically, ethically, temporally, spatially and philosophically. Data do not exist independently of the ideas, instruments, practices, contexts and knowledges used to generate, process and analyse them* (Kitchen, 2014a, p. 2) (Also see Boellstorff, 2013; De Zwardt, 2014; Pasquale, 2015; Uprichard, 2015).

This is illustrated by the fact that unless a dataset can be considered complete, that data remains *inherently partial, selective and representative, and the distinguishing criteria used in their capture has consequence* (Kitchen, 2014a, p. 3). While data, in the social imaginary, has become to be understood as representative of the total sample, objective and neutral, data is *different in nature to facts, evidence,* *information and knowledge* (Kitchen, 2014a, p. 3). Except for the fact that we can frame data technically and ethically, data also needs to be framed politically and economically that are used to discriminate against individuals, classes of people and geopolitical entities (Kitchen, 2014a, p. 15). (Also see Crawford, 2013; Henman, 2004; Selwyn & Facer, 2013; Uprichard, 2015).

DATA, BLACK BOXES AND ALGORITHMS

At the intersection of the deluge of data shared and collected by a variety of stakeholders and a growing reliance on predictive models are growing concerns about the ways in which algorithms now appear to shape our existence. As the reach, impact and downstream impacts of those algorithms become clearer (Eubanks, 2015; Henman, 2004; Kalhan, 2013; Pasquale, 2015), so too does the unease around accuracy, reliability and inherent biases (Bozdag, 2013; Diakopoulous, 2014a, 2014b; Friedman & Nissenbaum, 1996; Kitchen, 2014b; Pariser, 2011; Pasquale, 2011). While it falls outside of the scope of this chapter to fully explore this more fully, it is crucial that we again warn that 'here be dragons.'

Amidst the concerns regarding *algorithmic regulation* (Morozov, 2013, par.15) the *algorithmic turn*, (Napoli, 2013, p. 1), and the *threat of algocracy* (Danaher, 2014), scholars, researchers and policymakers are beginning to engage in debate around how best to control and regulate *automated authority* (Diakopoulous, 2014b, p. 12). Current strategies include (but are not limited to) data and algorithmic transparency, accountability and due process (Crawford & Schultz, 2014; Diakopoulous, 2014a; Koponen, 2015; Lohr, 2015; Seaver, 2013).

Given that many higher education institutions increasingly rely on algorithms to determine access, inform policy, personalise learning and support, and determine at-risk student populations (e.g., Cabral, Castolo, & Gallardo, 2015; Daniel, 2015; Prinsloo & Slade, 2013), we suggest a growing need to engage with the construct of student data.

ENGAGING WITH *STUDENT* DATA AS CONSTRUCT

Kitchen states that *data are a means by which political agendas and work can be legitimated, conducted and contested by enabling the construction of evidence-information narratives and counter-discourses that have great rhetorical value than anecdote or sentiment* (2014a, p. 16). If we accept this, we also accept that collecting and analysing is directly related to and in service of, inter alia, prevailing beliefs regarding student learning, policy frameworks as well as funding and regulatory regimes.

In the light of the accountability regimes and cost of funding for higher education as public good *[student] data can thus be understood as an agent of capital interests* (Kitchen, 2014a, p. 16). How then does this influence and shape our practices of selecting and analysing student data? If this data does not represent the whole reality of students' life and learning worlds, what does this mean for our analyses and interventions? If we accept that student data is not benign (Shah as cited in Kitchen, 2014a, p. 21) but should be understood as *framed and framing* (Gitelman & Jackson, as cited in Kitchen, 2014a, p. 21) – why are we so complacent about the analyses and the predictability models which flow from those analyses? The construct of student data therefore raises, inter alia, two important issues - namely our assumptions regarding student digital (non)activity and the 'situatedness' of that data.

Within higher education, students' digital footprints combined with their demographic details collected through registration and funding applications processes are often believed to represent the total picture of student potential and risk. Further, there is a belief that more data will, necessarily, provide a more holistic picture and result in better and more effective interventions (Prinsloo, Archer, Barnes, Chetty, & Van Zyl, 2015).

Indeed, it would seem that many theoretical frameworks and practices relating to learning analytics assume that the learning management system (LMS) provides a sufficient picture of student learning and that measuring activity, such as the number of clicks, time-on-task, or page views provides a direct correlation to student retention and success. (See Guillaume & Khachikian, 2011; Kovanović, Gašević, Dawson, Joksimović, Baker, & Hatala, 2015; Tempelaar, Rienties, & Giesbers, 2014). However, Kruse and Pongsajapan (2012) question this assumption that evidence of student activity on the LMS is a valid proxy for learning. (See also Godwin-Jones, 2012; Pardo & Kloos, 2011; Slade & Prinsloo, 2013).

Moreover, the notion that student digital data represents a total or holistic picture of the complexities of *students' learning* continues to gain acceptance, although surely questionable in the context of education as an open and recursive ecosystem. Not only is such data abstracted but also decontextualised - resulting in a loss of contextual integrity. Considering that *[c]ontexts are structured social settings characterised by canonical activities, roles, relationships, power structures, norms (or rules), and internal values (goals, ends, purposes)* (Nissenbaum, 2010, p. 132), there is a need to seriously question assumptions around student digital data as a reliable proxy or as fully representative. In a world seeking the elusive n=all data set, we should not accept that data showing student (dis)engagement on the LMS is sufficiently complete (Mayer-Schönberger & Cukier, 2013). (Also see Campbell, Chang, & Hosseinian-Far, 2015; Harford, 2014).

When we look at students' trajectories in higher education as *heterotopic spaces* (Foucault, 1984, p. 1), the notion of the LMS as representative of the total student journey becomes even more problematic. For researchers, the clear boundaries between public and private spaces are disappearing as we inhabit various spaces simultaneously (Rymarczuk & Derksen, 2014). Students concurrently live in physical worlds and digital worlds where their private (digital and non-digital) and public (digital and non-digital) lives intersect and become mutually constitutive. Our notions of synchronous and asynchronous, past and present lose their heuristic value and fundamentally contradict our assumptions and analyses. The assumption that student digital data collected from the LMS represents the 'reality' and allocate values to time-on-task, number of clicks, etc., disregards the LMS as a socially constructed space with its own norms, rules and activities (see Nissenbaum, 2010).

STUDENT DATA AND STUDENT RESPONSIBILITY

The *potential* benefits of learning analytics for increasing the effectiveness of learning are well-documented (Diaz & Brown, 2012; McKeown & Ayson, 2013; Oblinger, 2012; Siemens & Long, 2011). Durall & Gros (2014) state that analytics in education can be used to identify students at risk, provide recommendations to students to help personalise resources, reading and support, to *detect the need for, and measure the results of, pedagogic improvements*, to *identify teachers who are performing well, and teachers who need assistance with teaching methods* and to *assist in the student recruitment process*

(p. 380). (For a discussion on the difference between academic and learning analytics and their different potential, see Siemens & Long, 2011). We should remember and keep on reminding ourselves, that learning analytics is, primarily, about learning (Gašević, Dawson, & Siemens, 2015).

Central to a great deal of the literature highlighting the potential benefits of learning analytics is the notion of students and their learning trajectories as data *objects*. Students are portrayed in the main as *producers* of data and *recipients* of services and personalised learning journeys based on the availability of their digital data, the assumptions made and understanding of the complexities of learning, and analyses conducted. In addition, there is often also a worrying absence of concern regarding students' (lack of) knowledge of the collection of their data and any possible impact on their learning journeys. The only apparent requirement of students to engage in their role as data objects is to ensure that the demographic data which they provide is correct and current.

The current thinking about the scope of student responsibility may be influenced by the complexities of conceptualising student retention and success. Many models place the responsibility for student success on the ability of students to *fit into* the processes, epistemologies and pedagogical strategies of higher education (Prinsloo, 2009). This view of student involvement and responsibility stands in stark contrast to the conceptual model proposed by Subotzky and Prinsloo (2011) who suggest that students are not mere recipients of services, but active agents in a reciprocal social contract with higher education.

The underlying notion of students as passive recipients of services and as objects of interventions is amplified when the *constant language of 'intervention' perpetuates an institutional culture of students as passive subjects – the targets of a flow of information – rather than self-reflective learners given the cognitive tools to evaluate their own learning processes* (Kruse & Pongsajapan, 2012, p. 2) (Also see Gašević et al., 2015). If instead we see student success as *the outcome of the mutually influential activities, behaviours, attitudes, and responsibilities of students and the institution, which are viewed in the sociological perspective of situated agents* (Subotzky & Prinsloo, 2011, p. 184), it is clear that any assumptions of students as (just) producers of data must be revised. (Also see Slade & Prinsloo, 2013; Prinsloo & Slade 2015a, 2015b).

STUDENT-CENTRED LEARNING ANALYTICS

While the notion of student-centred analytics has not gained wide traction in the discourses on educational mining and learning analytics, a number of authors (Kruse & Pongsajapan, 2012; Slade & Prinsloo, 2014; Prinsloo & Slade, 2015a, 2015b) point to students not only making more informed choices regarding the information that they share, but also in holding their higher education institutions accountable for any subsequent analysis, and interpretation.

Engaging with the possibility and potential of students in learning analytics, Kruse and Pongsajapan (2012) propose that higher education needs to move from an *intervention-centric* approach to learning analytics and to reimagine analytics *in the service of learning [and] transform it into a practice characterised by a spirit of questioning and inquiry*. In this way, students become participants in the identification and gathering of their data as well as co-interpreters of their own data (p. 4). Durall and Gros (2014) support this view, stating that *very rarely are students considered the main receivers of the learning analytics data or given the opportunity to use the information to reflect on their learning activity and self-regulate their learning efficiently* (p. 382). Indeed, not only should students be given the possibility to verify their digital dossiers, but HEIs *should [also] provide mechanisms for learners* *to interact with these systems explicitly* (Durall & Gros, 2014, p. 382). (Also see Kump, Seifert, Beham, Lindstaedt, & Ley, 2012; Slade and Prinsloo (2013) go on to suggest that *valuing students as agents, making choices and collaborating with the institution in constructing their identities* is a positive approach *in the context of the impact of skewed power relations, monitoring, and surveillance* (p. 1520).

STUDENT DATA, AGENCY AND PRIVACY SELF-MANAGEMENT

It falls outside of the scope of this chapter to engage with the various definitions and regulatory frameworks which set out the protection of privacy. See for example, Gurses (2014), Marx (2001), Nissenbaum (2010), Tene and Polonetsky (2012) and Solove (2001, 2004, 2013) for discussion of the general context and specifically geopolitical and institutional contexts. However, it is possible to surmise that due to, inter alia, technological developments and changing social and cultural norms, the notion of privacy is *fluid* (Solove, 2013, p. 61).

Our discussion so far has suggested that users are in an asymmetrical power relationship to those different entities who collect, analyse and increasingly combine different sources of information. It would seem then that one of the few remaining ways for users to exercise their admittedly limited control over the collection and use of their data is by engaging with an organisation's Terms of Conditions (TOCs). Even so, it is broadly accepted that those TOCs are not particularly effective in ensuring either transparency or user control of that data, as those TOCs may be overly complex and/or lengthy (see, e.g., Bellman, Johnson, & Lohse, 2001, Prinsloo & Slade, 2015a). Furthermore, users must engage with separate TOCs on a case to case basis to an extent that the engagement becomes anything rational (Solove, 2013). The result is that users will often exchange their personal data for limited benefits.

Despite increasing sensitivity regarding surveillance and the use and sharing of personal data (PewResearchCenter, 2014) many users have become digitally promiscuous (Brian, 2015; Murphy, 2014). Against this backdrop, Prinsloo and Slade (2015a) present consent as a fragile concept. Despite this, Solove (2013) states that *Providing people with* notice, access, *and the* ability *to control their data is key to facilitating some autonomy in a world where decisions are increasingly made about them with the use of personal data, automated processes, and clandestine rationales, and where people have minimal abilities to do anything about such decisions* (p. 1899; emphasis added).

While we may think consent options as a straight binary choice between of opting in or opting out, Miyazaki and Fernandez (2000) suggest that there is a broader range of choice. *Possibilities of disclosure range from never collecting data or identifying customers when they access a site; customers opting in by explicitly agreeing to having their data collected, used and shared; customers explicitly opting out; the constant collection of data without consumers having a choice (but with their knowledge); to the collection, use and sharing of personal data without the user's knowledge* (Prinsloo & Slade, 2015a, par. 13). Despite this, it is also clear that once consent is provided in a particular context, however consensual and well understood, current legal frameworks do not protect user data when it is repurposed and reused in other contexts (Ohm, 2010, 2015).

Taking into account the fluidness of the notion of privacy and the fragility of the notion of consent, Greenwood et al.(2015) propose a *new deal on data* (p. 192) while Gurses (2014) suggests a *palette of 'privacy solution'* to allow individuals the agency to make more informed choices (Kerr & Barrigar, 2012).

A CASE STUDY OF OPEN UNIVERSITY POLICY

While the ethical considerations of research on students are covered extensively in research policies with ample consideration of 'doing no harm' there is very little or no consideration of the ethical or harm considerations in the use of learning analytics within higher education (Prinsloo & Slade, 2013).

Many learning analytics strategies focus on informing students of the uses of their data, but as Solove (2013) indicates, privacy policies are not always read or well understood. Indeed, there is little formal evidence that students are explicitly consulted or even loosely aware of the broader uses of their data beyond research. The Open University in the UK is an open, distance learning university supporting over 200,000 students each year. Like many other HEIs, the Open University is making increasing use of its student data and became aware that this position was not adequately described within existing policy. To that end, the development of a new institutional policy was commissioned to address ethical issues relating to its approach to learning analytics.

A thorough review of the literature and of existing external practice within the higher education sector was conducted which indicated little evidence of other new policy development beyond that required under national legislation. Themes and issues from the review were used to develop a set of eight broad guiding principles, describing key tenets and values of the University's approach to student support and of the use of data to guide and shape that support.

The creation of any new institutional policy, of necessity, requires considerable consultation combined with a formal and iterative approval process. A small working group of staff with expertise and authority in relevant areas met frequently taking shared ownership of tasks. Key stakeholders were consulted at an early stage on the eight principles. This initial consultation specifically included a few elected student representatives to ameliorate concerns that broader inclusion of students might introduce disquiet at a point when issues had not been thoroughly appraised. Once a coherent draft was agreed, the policy was circulated to a larger group of students via a formal consultation process to uncover student attitudes to their data, and specific issues such as privacy and scope.

The student perspective was crucial, offering both direct insight and understanding of the need for transparency and informed consent. Capturing the student voice clarified key issues and emphasised a need to consider seriously the issue of opt-out. However, this particular issue was not easily resolved. Opt-out introduces significant systems issues, but also unearths a specific moral conflict. Some staff felt strongly that opt-out would render the University unable to act in students' best interests (considered unethical in itself), whilst others felt that students, as active and adult learners, should have rights to determine their own support. As a result, the policy was approved in July 2014, with the condition that the specific issue of consent be reviewed within a year.

The new policy has been clearly communicated to all stakeholder groups. For many students, the emergence of the policy has highlighted for the first time the uses being made of their data. The formal consultation yielded insight that many were unaware that any of their data was collected and used for monitoring or tracking purposes, and it has been clear that there is significant unease regarding the ways in which personal data might be used. Managing the communication process has required a sensitive balance - with the need to both reveal longstanding and ongoing practices, and, at the same time, to clarify and reassure students of the purposes, boundaries and potential benefits. Alongside the publication and communication of the policy, further staff resources were provided to ensure a practical understanding of how existing and planned activities might be impacted.

In retrospect, the emergence of the new policy has been both more straightforward and more complex than anticipated. Key to its creation and implementation has been the emergence of a high level champion, the input of a fully representative set of stakeholders and the awareness that the very creation of a policy flagging the activities undertaken is akin to opening a Pandora's box. Whilst the existence of the policy offers some sense of moral comfort for the University, it is clear that ongoing work will be needed to ensure that the changing legislative environment is adhered to and that the student voice continues to be heard and reflected.

GENERAL PRINCIPLES FOR A NEW DEAL ON STUDENT DATA IN LEARNING ANALYTICS

So far we have attempted to open up the constructs of student data, student responsibility and their involvement in learning analytics and to look at a case study of an institutional response to the complexities and practicalities of the use of student data in teaching and learning contexts.

If HEIs are to successfully rethink students' roles and participation in learning analytics, they must accept a new dispensation where students are no longer (only) the producers of data and data objects, but *participating* agents. Prinsloo and Slade (2015a) propose a number of principles for HEIs to move beyond a paternalistic approach to the collection, analysis and use of student data, to a discursive-disclosive approach (Stoddart, 2012). In discussing Prinsloo and Slade's (2015a) suggested principles, we specifically focus on the *agency* and *responsibility* of students.

The Duty of Reciprocal Care

The asymmetrical power relationship between students and HEIs necessitates that we seriously consider the *ethical* dimensions and impact of this asymmetry. With HEIs currently cast in the role of provider, it is clear that the imperative for an ethical approach to the use of student data lies within the locus of control of HEI. As students become increasingly aware of and concerned about the collection and use of their data (Slade & Prinsloo, 2013), we argue that HEIs have a fiduciary duty to respond.

HEIs can, amongst other things, make their TOCs more accessible and understandable; make clear the scope, timing, use, governance and conditions of sharing student data and information; and provide students with recourse in case of privacy breaches. The TOCs should, however, also reimagine the role and responsibility of students to not only empower students with actionable information, but also allow them to verify data, provide context, and provide additional information.

The Contextual Integrity of Student Data

Earlier we established the importance of context in considering the collection, analysis and use of student data. Student engagement on an institutional LMS does not represent a holistic picture of students' learning and/or progress. Any measure of LMS activity such as students' sharing of data and their time-on-task, number of clicks and page views should also consider the embedded rules, conventions and norms of engagement.

Should data from students' activity *outside* of the LMS be collected and analysed, it is crucial to remember that information shared in one context and for a specific context-specific purpose may not be transferable to other contexts (see Nissenbaum, 2010). While there are increasing claims regarding the potential of combining different sources and databases, and for the repurposing of data sets (Long, 2014), we cannot and should not disregard the social contract between higher education and its students.

Rethinking Student Agency and Consent

In seeking to move toward students as active agents, we should first rethink the ways in which students are more practically able to become involved in their HEIs' approaches to learning analytics. One perspective on this might be to examine how students are able to grant consent to their involvement. We suggest that effective privacy self-management requires a more nuanced approach to that of the simple binary of opting in or out. Students may, for example, agree to share data in specific contexts or may agree to share specific aspects of their learning experiences if they are given a clear understanding of the details of data collection, e.g., the scope of data collected, who will have access, under which conditions, for how long and for what purpose (Prinsloo & Slade, 2015a). (Also see Solove, 2013). Prinsloo and Slade (2015a) suggest that, despite some residual concerns, nudging students to share their data with clear guidance on the purpose and benefits of such sharing would be an improvement on current practice in learning analytics where students largely don't know and have no choice.

Adjusting Privacy's Timing and Focus

Accepting the importance of contextual integrity and guarding against context-collapse (Nissenbaum, 2010), we suggest that students should be informed regarding aspects such as how long their data will be kept in personalised forms, for what purposes their data may be used and shared downstream. While students may provide consent at the time of the collection of their data, they may have legitimate concerns regarding other uses of their data outside of the original context and timing of the initial collection. Prinsloo and Slade (2015) therefore suggest that HEIs should provide students with a range of options *such as outright restrictions, partial consent which may depend on the scope, context and timing, and permission to harvest and use data, with an option to later revoke consent or change the scope of consent depending on the context or circumstances* (p. 90).

Moving Toward Substance Over Neutrality

Amidst tensions between paternalistic or rule-based considerations of user data privacy and discursive-disclosive approaches (Stoddart, 2012), there is a need for clear and enforceable legislation and regulatory frameworks to prevent gross misuse and unfair practices. Alongside this, it might be argued, there is also a need for flexible, case-by-case and context-appropriate guidelines. Given that ordinary users are unlikely to have the resources or access to legal advice to enforce due process if feeling aggrieved or if rights to privacy and data protection are breached, the introduction of institutional guidelines offers some protection against the potential for harm.

From Quantified Selves to Qualified Selves

In the broader context of a *quantification fetish* (Prinsloo, 2014) in higher education, there is greater potential to collect, analyse and use student data, it is crucial that we keep in mind that students are more than their data (e.g., Carney, 2013). The danger is that students become quantified selves based on the number of their log-ins, clicks, downloads, time-on-task and various other data points (Prinsloo & Slade, 2015b). Ideally we should aim to move from quantified selves to qualified selves (e.g., Boam & Webb, 2015; Davies, 2013; Li, Dey, & Forlizzi, 2011; Lupton, 2014a, 2014b; Prinsloo & Slade, 2015b). *Where the quantified self gives us the raw numbers, the qualified self completes our understanding of those numbers* (Boam & Webb, 2015, par. 8). Our students are therefore much more than just conglomerates of quantifiable data (e.g., Lupton, 2014b) and it is important that we take into account *the contexts in which numbers are created* (Lupton, 2014b, p. 6).

CONCLUSION

There is a danger that amidst the hype regarding Big Data in general, and specifically learning analytics in the context of higher education, we don't acknowledge a number of blind spots (Selwyn & Facer, 2013). In this chapter we have attempted to highlight some of these and to warn that 'here be dragons.' Despite those dragons, the blind spots and a myriad of as yet unresolved issues with regard to privacy and the ethical implications of learning analytics, we are of the firm opinion that higher education cannot afford (often literally) *not* to collect, analyse and to use student data (Slade & Prinsloo, 2014).

Given that higher education is a moral endeavour and that higher education has a fiduciary duty towards caring for students, it is clear that the issue is not whether higher education should collect, analyse and use student data, but *under what conditions*.

Although we would suggest that there are some clear principles which may be considered in involving students in the collection, analysis and use of their data, we would also acknowledge that there are a number of remaining uncertainties and practicalities that deserve exploration and further investigation. Some of these include consideration of the implications and scalability of allowing students to opt in to some data collection and analyses, while opting out of others. What are the implications when students opt in, and then after a period of time, decide to opt out?

Students' digital dossiers are only a part of their learning trajectories and provide but glimpses of their activities in an increasingly open and recursive system where their engagement or disengagement flows from mutually constitutive and interdependent variables. It is clear that our assumptions about time-on-task, their number of clicks and page views are nothing more than peeks into the unknown and that there are still many unchartered territories in student learning.

REFERENCES

Altbach, P. G., Reisberg, L., & Rumbley, L. E. (2009). Trends in global higher education: tracking an academic revolution. A report prepared for the UNESCO World Conference on Higher Education. Paris: UNESCO. Retrieved from http://atepie.cep.edu.rs/public/Altbach,_Reisberg,_Rumbley_Tracking_an_Academic_Revolution,_UNESCO_2009.pdf

Antón, A. I., & Earp, J. B. (2004). A requirements taxonomy for reducing web site privacy vulnerabilities. *Requirements Engineering*, *9*(3), 169–185. doi:10.1007/s00766-003-0183-z

Barnes, T. J. (2013). Big Data, little history. *Dialogues in Human Geography*, *3*(3), 297–302. doi:10.1177/2043820613514323

Bellman, S., Johnson, E. J., & Lohse, G. L. (2001). On site: to opt-in or opt-out?: it depends on the question. *Communications of the ACM*, *44*(2), 25–27. Retrieved from http://dl.acm.org/citation.cfm?id=359241 doi:10.1145/359205.359241

Biesta, G. (2007). Why "what works" won't work: Evidence-based practice and the democratic deficit in educational research. *Educational Theory*, *57*(1), 1–22. doi:10.1111/j.1741-5446.2006.00241.x

Biesta, G. (2010). Why 'what works' still won't work: From evidence-based education to value-based education. *Studies in Philosophy and Education*, *29*(5), 491–503. doi:10.1007/s11217-010-9191-x

Boam, E., & Webb, J. (2015). The qualified self: going beyond quantification [Blog comment]. Retrieved from http://designmind.frogdesign.com/articles/the-qualified-self-going-beyond-quantification.html

Boellstorff, T. (2013). Making big data, in theory. *First Monday*, *18*(10). http://firstmonday.org/ojs/index.php/fm/article/view/4869 doi:10.5210/fm.v18i10.4869

Booth, M. (2012, July 18). Learning analytics: the new black. *EDUCAUSEreview*. Retrieved from http://www.educause.edu/ero/article/learning-analytics-new-black

Bowen, E. G., & Lack, K. A. (2013). *Higher education in the digital age*. Princeton, N.J.: Princeton University Press. doi:10.1515/9781400847204

Boyd, D., & Crawford, K. (2012). Critical questions for Big Data. *Information Communication and Society*, *15*(5), 662–679. doi:10.1080/1369118X.2012.678878

Boyd, D., & Crawford, K. (2013). Six provocations for Big Data. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1926431

Bozdag, E. (2013). Bias in algorithmic filtering and personalization. *Ethics and Information Technology*, *15*(3), 209–227. doi:10.1007/s10676-013-9321-6

Brian, S. 2015. The unexamined life in the era of big data: toward a UDAAP for data. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2533068

Cabral, S. R., Castolo, J. C. G., & Gallardo, S. C. H. (2015, January). Algorithm to optimize a fuzzy model of students' academic achievement in higher education. In *Congreso Virtual sobre Tecnología. Education et Sociétés*, *1*(4).

Campbell, J., Chang, V., & Hosseinian-Far, A. (2015). Philosophising data: A critical reflection on the 'hidden' issues. [IJOCI]. *International Journal of Organizational and Collective Intelligence*, *5*(1), 1–15. doi:10.4018/IJOCI.2015010101

Carney, M. (2013). You are your data: the scary future of the quantified self movement [Blog comment]. Retrieved from http://pando.com/2013/05/20/you-are-your-data-the-scary-future-of-the-quantified-self-movement/

Carr, N. (2012). The crisis in higher education. *Technology Review*. Retrieved from http://www.technologyreview.com/featuredstory/429376/the-crisis-in-higher-education/

Christensen, C. (2008). Disruptive innovation and catalytic change in higher education. Forum for the Future of Higher Education. *EDUCAUSE*. Retrieved from https://net.educause.edu/ir/library/pdf/ff0810s.pdf

Clow, D. (2013a). An overview of learning analytics. *Teaching in Higher Education*, *18*(6), 683–695. doi:10.1080/13562517.2013.827653

Clow, D. (2013b, November 13). Looking harder at Course Signals [Blog comment]. Retrieved from http://dougclow.org/2013/11/13/looking-harder-at-course-signals/

Crawford, K. (2013, April 1). The hidden biases in big data. [Web log comment]. Harvard Business Review. Retrieved from http://blogs.hbr.org/cs/2013/04/the_hidden_biases_in_big_data.html

Crawford, K., & Schultz, J. (2014). Big data and due process: Toward a framework to redress predictive privacy harms. *BCL Rev.*, *55*, 93–128.

Danaher, J. (2014). Rule by algorithm? Big data and the threat of algocracy. Institute for Ethics and Emerging Technologies. [Blog comment]. Retrieved from http://philosophicaldisquisitions.blogspot.com/2014/01/rule-by-algorithm-big-data-and-threat.html

Daniel, B. (2015). Big Data and analytics in higher education: Opportunities and challenges. *British Journal of Educational Technology*, *46*(5), 904–920. doi:10.1111/bjet.12230

Davies, J. (2013, March 13). The qualified self [Blog comment]. Retrieved from http://thesocietypages.org/cyborgology/2013/03/13/the-qualified-self/

De Zwart, H. (2014, May 5). During World War II, we did have something to hide. (Translated by Benjamin van Gaalen). Retrieved from https://www.bof.nl/2015/04/30/during-world-war-ii-we-did-have-something-to-hide/

Diakopoulos, N. (2014a). Algorithmic Accountability Reporting: On the Investigation of Black Boxes. Tow Center. Retrieved from http://www.nickdiakopoulos.com/wp-content/uploads/2011/07/Algorithmic-Accountability-Reporting_final.pdf

Diakopoulos, N. (2014b). Algorithmic Accountability: Journalistic investigation of computational power structures. *Digital Journalism*.

Diaz, V., & Brown, M. (2012). Learning analytics. A report on the ELI focus session. Retrieved from http://net.educause.edu/ir/library/PDF/ELI3027.pdf

Durall, E., & Gross, B. (2014). Learning analytics as a metacognitive tool. Retrieved from https://files.ifi.uzh.ch/stiller/CLOSER_2014/CSEDU/CSEDU/Information_Technologies_Supporting_Learning/Short Papers/CSEDU_2014_152_CR.pdf

Earp, J. B., Antón, A. I., Aiman-Smith, L., & Stufflebeam, W. H. (2005). Examining Internet privacy policies within the context of user privacy values. *Engineering Management*. *IEEE Transactions on*, *52*(2), 227–237.

Essa, A. (2013). Can we improve retention rates by giving students chocolates? [Blog comment]. Retrieved from http://alfredessa.com/2013/10/can-we-improve-retention-rates-by-giving-students-chocolates/

Eubanks, V. (2015, April 30). The policy machine. Slate Magazine. Retrieved from http://www.slate.com/articles/technology/future_tense/2015/04/the_dangers_of_letting_algorithms_enforce_policy.html

Eynon, R. (2013). The rise of Big Data: What does it mean for education, technology, and media research? *Learning, Media and Technology*, *38*(3), 237–240. doi:10.1080/17439884.2013.771783

Feldstein, M. (2013, November 6). Purdue's non-answer on Course Signals [Blog comment]. Retrieved from http://mfeldstein.com/purdues-non-answer-course-signals/

Foucault, M. (1984). Of other spaces. Utopias and heterotopias. In *Architecture/Mouvement/Continuité, Des Espace Autres* (1967, March). (trans. by J. Miskowiec). Retrieved from http://web.mit.edu/allanmc/www/foucault1.pdf

Friedman, B., & Nissenbaum, H. (1996). Bias in computer systems. *ACM Transactions on Information Systems*, *14*(3), 330–347. doi:10.1145/230538.230561

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends*, *59*(1), 64–71. doi:10.1007/s11528-014-0822-x

Godwin-Jones, R. (2012). Challenging Hegemonies in Online Learning. *Language Learning & Technology*, *16*(2), 4.

Greenwood, D., Stopczynski, A., Sweat, B., Hardjono, T., & Pentland, A. (2015). The new deal on data: a framework for institutional controls. In J. Lane, V. Stodden, S. Bender, & H. Nissenbaum (Eds), Privacy, big data, and the public good (pp. 192-210). New York, NY: Cambridge University Press.

Guillaume, D. W., & Khachikian, C. S. (2011). The effect of time on task on student grades and grade expectations. *Assessment & Evaluation in Higher Education*, *36*(3), 251–261. doi:10.1080/02602930903311708

Gurses, S. (2014). Privacy and security. Can you engineer privacy? Viewpoints. *Communications of the ACM*, *57*(8), 20–23. Retrieved from http://dl.acm.org/citation.cfm?id=2632661.2633029 doi:10.1145/2633029

Harford, T. (2014). Big data: are we making a big mistake. *Financial Times*, 28, 1-5.

Hartley, D. (1995). The 'McDonaldization' of higher education: Food for thought? *Oxford Review of Education*, *21*(4), 409–423. doi:10.1080/0305498950210403

Henman, P. (2004). Targeted! Population segmentation, electronic surveillance and governing the unemployed in Australia. *International Sociology*, *19*(2), 173–191. doi:10.1177/0268580904042899

Hillman, N. W., Tandberg, D. A., & Fryar, A. H. (2015). Evaluating the impacts of "new" performance funding in higher education. *Educational Evaluation and Policy Analysis*.

Kalhan, A. (2013). Immigration policing and federalism through the lens of technology, surveillance, and privacy. *Ohio State Law Journal*, *74*, 1105–1165.

Kerr, I., & Barrigar, J. (2012). Privacy, identity and anonymity. In K. Ball, K. D. Haggerty, & D. Lyon (Eds.), *Routledge Handbook of Surveillance Studies* (pp. 386–394). Abingdon, UK: Routledge. doi:10.4324/9780203814949.ch4_1_c

Kitchen, R. (2014a). *The data revolution. Big data, open data, data infrastructures and their consequences*. London, UK: SAGE. doi:10.4135/9781473909472

Kitchen, R. (2014b). Thinking critically about and research algorithms. The Programmable City Working Paper 5. Retrieved from http://eprints.maynoothuniversity.ie/5715/

Koponen, J. M. (2015, April 18). We need algorithmic angels [Blog comment]. *TechCrunch*. Retrieved from http://techcrunch.com/2015/04/18/we-need-algorithmic-angels/

Kovanović, V., Gašević, D., Dawson, S., Joksimović, S., Baker, R. S., & Hatala, M. (2015, March). Penetrating the black box of time-on-task estimation. *Proceedings of the Fifth International Conference on Learning Analytics and Knowledge* (pp. 184-193). ACM. doi:10.1145/2723576.2723623

Kruse, A., & Pongsajapan, R. (2012). Student-centered learning analytics. Retrieved from https://cndls.georgetown.edu/m/documents/thoughtpaper-krusepongsajapan.pdf

Kump, B., Seifert, C., Beham, G., Lindstaedt, S. N., & Ley, T. (2012, April). Seeing what the system thinks you know: visualizing evidence in an open learner model. *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (pp. 153-157). ACM. doi:10.1145/2330601.2330640

Lane, J., Stodden, V., Bender, S., & Nissenbaum, H. (Eds.). (2014). *Privacy, big data, and the public good*. New York, NY: Cambridge University Press. doi:10.1017/CBO9781107590205

Li, I., Dey, A. K., & Forlizzi, J. (2011, September). Understanding my data, myself: supporting self-reflection with ubicomp technologies. *Proceedings of the 13th international conference on Ubiquitous computing* (pp. 405-414). ACM. doi:10.1145/2030112.2030166

Lohr, S. (2015, April). How much should humans intervene with the wisdom of algorithms [Blog comment]. Retrieved from http://www.afr.com/technology/how-much-should-humans-intervene-with-the-wisdom-of-algorithms-20150407-1mfqiw

Long, S. (2014, February 20). 'Re-purposing data' in the digital humanities [Blog comment]. Retrieved from https://technaverbascripta.wordpress.com/2014/02/20/re-purposing-data-in-the-digital-humanities/

Lupton, D. (2014a, July 28). Beyond the quantified self: the reflexive monitoring self [Blog comment]. Retrieved from https://simplysociology.wordpress.com/2014/07/28/beyond-the-quantified-self-the-reflexive-monitoring-self/

Lupton, D. (2014b). You are your data: self-tracking practices and concepts of data. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2534211

Marx, G. T. (2001). Murky conceptual waters: The public and the private. *Ethics and Information Technology*, *3*(3), 157–169. doi:10.1023/A:1012456832336

Mayer-Schönberger, V., & Cukier, K. (2013). *Big data. A revolution that will transform how we live, work, and think*. New York, N.Y.: Houghton Miffling Harcourt Publishing Company.

McKeown, T., & Ayson, S. (2013, December 4-6). *Unleashing the potential of learning analytics: A project outline and a model to put the student first*. Paper presented at the Australian and New Zealand Academy of Management (ANZAM) Conference, Hobart, Australia. Retrieved from http://funrun.gcc.tas.gov.au/anzam/content/pdfs/anzam-2013-398.pdf

Mehta, P. (2015, March 12). Big Data's radical potential. *Jacobin Magazine*. Retrieved from https://www.jacobinmag.com/2015/03/big-data-drones-privacy-workers/

Miyazaki, D., & Ferenandez, A. (2000). Internet privacy and security: An examination of online retailer disclosures. *Journal of Public Policy & Marketing*, *19*(1), 54–61. doi:10.1509/jppm.19.1.54.16942

Morozov, E. (2013a, October 23). The real privacy problem. *MIT Technology Review*. Retrieved from http://www.technologyreview.com/featuredstory/520426/the-real-privacy-problem/

Murphy, K. (2014, October 4). We want privacy, but can't stop sharing. The New York Times [Blog comment]. Retrieved from http://www.nytimes.com/2014/10/05/sunday-review/we-want-privacy-but-cant-stop-sharing.html

Napoli, P. (2013). The algorithm as institution: Toward a theoretical framework for automated media production and consumption. *Proceedings of the Media in Transition Conference* (pp. 1–36). DOI: doi:10.2139/ssrn.2260923

New Media Consortium. (2015). Horizon report higher education edition. Retrieved from https://net.educause.edu/ir/library/pdf/HR2015.pdf

Nissenbaum, H. (2010). *Privacy in context. Technology, policy, and the integrity of social life*. Stanford, CA: Stanford Law Books.

Oblinger, D. G. (2012). Let's talk analytics. *EDUCAUSEreview*. Retrieved from http://www.educause.edu/ero/article/lets-talk-analytics

Ohm, P. (2010). Broken promises of privacy: Responding to the surprising failure of anonymisation. *UCLA Law Review. University of California, Los Angeles. School of Law*, *57*, 1701–1777. Retrieved from http://heinonline.org/HOL/Page?handle=hein.journals/uclalr57&div=48&g_sent=1&collection=journals

Ohm, P. (2015). Changing the rules: general principles for data use and analysis. In J. Lane, V. Stodden, S. Bender, & H. Nissenbaum (Eds.), *Privacy, big data, and the public good* (pp. 96–111). New York, NY: Cambridge University Press.

Open University. (2014). Policy on ethical use of student data for learning analytics. Retrieved from http://www.open.ac.uk/students/charter/essential-documents/ethical-use-student-data-learning-analytics-policy

Pardo, A., & Kloos, C. D. (2011, February). Stepping out of the box: towards analytics outside the learning management system. *Proceedings of the 1st International Conference on Learning Analytics and Knowledge* (pp. 163-167). ACM. doi:10.1145/2090116.2090142

Pardo, A., & Siemens, G. (2014). Ethical and privacy principles for learning analytics. *British Journal of Educational Technology*, *45*(3), 438–450. doi:10.1111/bjet.12152

Pariser, E. (2011). *The filter bubble. What the Internet is hiding from you*. London, UK: Viking.

Pasquale, F. (2015). *The black box society: the secret algorithms that control money and information*. London, UK: Harvard University Press. doi:10.4159/harvard.9780674736061

Pasquale, F. A. (2011). *Restoring Transparency to Automated Authority*. Seton Hall Research Paper, (2010-28).

PewResearchCenter. (2014). Public perceptions of privacy and security in the post-Snowden era. Retrieved from http://www.pewinternet.org/2014/11/12/public-privacyperceptions/

Prinsloo, P. (2009). Modelling Throughput at Unisa: The key to the successful implementation of ODL. Retrieved from http://uir.unisa.ac.za/handle/10500/6035

Prinsloo, P. (2014). *A brave new world: student surveillance in higher education*. Presentation at the Annual Conference of the Southern African Association for Institutional Research (SAAIR) Conference 16-18 October, Pretoria, South Africa. Retrieved from http://www.slideshare.net/prinsp/a-brave-new-world-student-surveillance-in-higher-education

Prinsloo, P., Archer, E., Barnes, G., Chetty, Y., & Van Zyl, D. (2015). Big (ger) data as better data in open distance learning. *The International Review of Research in Open and Distributed Learning*, *16*(1), 284–306.

Prinsloo, P., & Slade, S. (2013, April). An evaluation of policy frameworks for addressing ethical considerations in learning analytics. *Proceedings of the Third International Conference on Learning Analytics and Knowledge* (pp. 240-244). ACM. doi:10.1145/2460296.2460344

Prinsloo, P., & Slade, S. (2014). Educational triage in open distance learning: Walking a moral tightrope. *The International Review of Research in Open and Distributed Learning*, *15*(4), 306–331.

Prinsloo, P., & Slade, S. (2015, b). *Student vulnerability, agency and learning analytics: an exploration*. Presented at the EP4LA workshop during the Fifth International Conference on Learning Analytics and Knowledge.

Prinsloo, P., & Slade, S. (2015a, March). Student privacy self-management: implications for learning analytics. *Proceedings of the Fifth International Conference on Learning Analytics and Knowledge* (pp. 83-92). ACM. doi:10.1145/2723576.2723585

Rymarczuk, R., & Derksen, M. (2014). Different spaces: Exploring Facebook as heterotopia. *First Monday*, *19*(6). Retrieved from http://firstmonday.org/ojs/index.php/fm/article/view/5006/4091 doi:10.5210/fm.v19i6.5006

Seaver, N. (2013). Knowing Algorithms. *Media in Transition*, *8*, 1–12.

Selwyn, N. (2015). Data entry: Towards the critical study of digital data and education. *Learning, Media and Technology*, 40(1).

Selwyn, N., & Facer, K. (Eds.). (2013). *The politics of education and technology*. New York: Palgrave Macmillan. doi:10.1057/9781137031983

Shirky, C. (2014, January 29). The end of higher education's golden age. [Blog comment}. Retrieved from http://www.shirky.com/weblog/2014/01/there-isnt-enough-money-to-keep-educating-adults-the-way-were-doing-it/

Siemens, G. (2013). Learning analytics: The emergence of a discipline. *The American Behavioral Scientist*, *57*(10), 1380–1400. doi:10.1177/0002764213498851

Siemens, G., & Long, P. (2011). Penetrating the fog: Analytics in learning and education. *EDUCAUSE Review*. Retrieved from http://www.educause.edu/ero/article/penetrating-fog-analytics-learning-and-education

Slade, S., & Prinsloo, P. (2013). Learning analytics ethical issues and dilemmas. *The American Behavioral Scientist*, *57*(10), 1510–1529. doi:10.1177/0002764213479366

Solove, D. J. (2001). Privacy and power: Computer databases and metaphors for information privacy. *Stanford Law Review*, *53*(6), 1393–1462. doi:10.2307/1229546

Solove, D. J. (2004). *The digital person. Technology and privacy in the information age*. New York, NY: New York University Press.

Solove, D. J. (2013). Introduction: Privacy self-management and the consent dilemma. *Harvard Law Review* 1880 GWU Legal Studies Research Paper No. 2012-141. Retrieved from http://ssrn.com/abstract=2171018

Stiles, R. J. (2012). Understanding and managing the risks of analytics in higher education: A guide. *EDUCAUSE*. Retrieved from https://net.educause.edu/ir/library/pdf/EPUB1201.pdf

Stoddart, E. (2012). A surveillance of care. Evaluating surveillance ethically. In K. Ball, K. D. Haggerty, & D. Lyon (Eds.), *Routledge Handbook of Surveillance Studies* (pp. 369–376). Abindgon, UK: Routledge. doi:10.4324/9780203814949.ch4_1_a

Subotzky, G., & Prinsloo, P. (2011). Turning the tide: A socio-critical model and framework for improving student success in open distance learning at the University of South Africa. *Distance Education*, *32*(2), 177–193. doi:10.1080/01587919.2011.584846

Tait, A. (2015). Student success in open, distance and e-learning. ICDE Report Series. Retrieved from http://icde.org/admin/filestore/Resources/Studentsuccess.pdf

Tempelaar, D. T., Rienties, B., & Giesbers, B. (2014). In search for the most informative data for feedback generation: Learning Analytics in a data-rich context. *Computers in Human Behavior*. Retrieved from http://www.sciencedirect.com/science/article/pii/S0747563214003240

Tene, O., & Polonetsky, J. (2012). Big data for all: Privacy and user control in the age of analytics. *Northwestern Journal of Technology and Intellectual Property, 239*, 1–36. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2149364

Uprichard, E. (2015, February 12). Philosophy of data science - Most big data is social data – the analytics need serious interrogation. *Impact of Social Sciences*. Retrieved from http://blogs.lse.ac.uk/impactofsocialsciences/2015/02/12/philosophy-of-data-science-emma-uprichard/

Van Rijmenam, M. (2013, April 30). Big data will revolutionise learning [Blog comment]. Retrieved from http://smartdatacollective.com/bigdatastartups/121261/big-data-will-revolutionize-learning

Wagner, E., & Ice, P. (2012, July 18). Data changes everything: delivering on the promise of learning analytics in higher education. *EDUCAUSEreview*. Retrieved from http://www.educause.edu/ero/article/data-changes-everything-delivering-promise-learning-analytics-higher-education

Watters, A. (2013, October 13). Student data is the new oil: MOOCs, metaphor, and money [Blog comment]. Retrieved from http://www.hackeducation.com/2013/10/17/student-data-is-the-new-oil/

Wishon, G. D., & Rome, J. (2012, 13 August). Enabling a data-driven university. *EDUCAUSE review*. Retrieved from http://www.educause.edu/ero/article/enabling-data-driven-university

ENDNOTES

[1] Though *data* as the plural of *datum* have traditionally been treated as plural, data is increasingly used as a phenomenon and therefore *singular*. In this chapter we therefore refer to data as singular unless used as plural in quotations.