

Chapter 79

Here Be Dragons: Mapping Student Responsibility in Learning Analytics

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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,

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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

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