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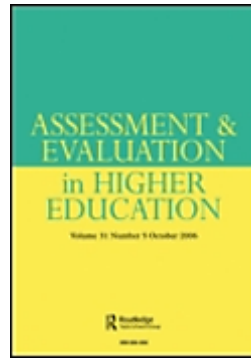
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For Peer Review Only

## **Empowering learners with personalised learning approaches? Agency, equity and transparency in the context of learning analytics**

### **Abstract**

The emergence of personalised data technologies, such as learning analytics (LA) is framed as a solution to manage the needs of higher education student populations that are growing ever more diverse and larger in size. However, the current approach to learning analytics presents tensions between increasing student agency in making learning-related decisions and ‘datafying’ students in the process of collecting, analysing and interpreting data. This paper presents a study that explores staff and student experience of agency, equity, and transparency in existing data practices and expectations towards LA in a UK university. The results show a number of intertwined factors that have contributed to the tensions between enhancing a learner’s control of their studies and, at the same time, diminishing their autonomy as an active agent in the process of LA. This paper argues that learner empowerment should not be automatically assumed to have taken place as part of the adoption of learning analytics. Instead, the interwoven power relationships in a complex educational system and the interactions between humans and machines need to be taken into consideration when presenting LA as an equitable process to enhance student agency and educational equity.

**Keywords:** learning analytics, agency, equity, transparency

### **Introduction**

In education, the trend towards data-based methods of governance and management initially led to a thriving field of educational data mining, concerned with the automated exploration of data from educational settings (Siemens and Baker 2012). Later, it enabled the emergence of Learning Analytics (henceforth LA) as a distinct field of research and practice that aims to use data to optimise learning and the environments where it occurs (Long et al. 2011). While LA shows great potential in tackling educational challenges of attainment and student retention, there are also prevailing concerns around the ethical and privacy implications of the use of student data, and the extent to which LA can benefit every student (Tsai, Moreno-Marcos, Jivet, et al. 2018).

A key problem with current approaches to LA lies in the tensions between increasing student agency in making learning-related decisions and ‘datafying’ students in the process of collecting, analysing and interpreting data. On the one hand, digital technologies in education have been associated with the rise of a distinct form of market-based individualism, which shifts

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3 the traditional values of education from public good to private interest (Castañeda and Selwyn  
4 2018). This frames learning as a self-centred endeavour and investment (Thompson and Cook  
5 2017), with learners entrusted with more responsibility to improve their own performance  
6 through technology-enhanced support. On the other hand, the indiscriminate collection and  
7 analysis of student data from digital learning environments risks disregarding human factors and  
8 the socio-cultural contexts in which the data is generated (Perrotta 2013; Gašević, Dawson, and  
9 Siemens 2015). These tensions bring to the fore an urgent need for a critical discourse to further  
10 examine the paradoxical promises of LA in enhancing student agency, while furthering a  
11 pervasive governance culture of data collection, interpretation, and intervention design, thereby  
12 contentiously exercising ‘algorithmic control’ over education.

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19 In this paper, we argue that learner empowerment should not be automatically assumed  
20 to have occurred through the adoption of personalised data technologies such as LA. Instead,  
21 the interwoven power relationships in a complex educational system and the interactions  
22 between humans and machine need to be taken into consideration when presenting LA as an  
23 equitable process to enhance student agency and educational equity. We reflect on the  
24 aforementioned issues by drawing on data collected from six student focus groups (26  
25 participants in total) and 5 staff focus groups (18 participants in total) carried out in a UK higher  
26 education institution. The analysis was informed by two research questions:

- 27 1. How might personalised data technologies enhance or hamper equity and agency?
- 28 2. How might existing and expected transparency of data practices strengthen or compromise  
29 student agency?

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39 With the first question, we intend to draw attention to the prevailing assumption that  
40 personalised data technologies can empower learners (Kurilovas, Krikun, and Melesko 2016;  
41 Mouri et al. 2016; Charleer et al. 2018). This assumption is widespread, despite some evidence  
42 suggesting that presenting students with their own data can have a negative impact on  
43 motivations and chances of academic success (Lonn, Aguilar, and Teasley 2015). In line with  
44 this more critical research, we examine this assumption from the aspects of equity and agency in  
45 the context of LA. The second question explores the presence of student agency by looking into  
46 the control of their own data. In particular, we present issues on information asymmetries  
47 between data collectors and data subjects due to power imbalance (Acquisti and Grossklags  
48 2007; Rubel and Jones 2016). This paper critically examines the extent to which learning  
49 analytics can be used to enhance student agency and educational equity.

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57 In the next section, we discuss key concepts of datafication, agency, equity and  
58 transparency, drawing on relevant contributions from various disciplinary perspectives,  
59 including critical sociology. Thereafter, we present the participants’ experience of agency,  
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3 equity, and transparency in existing data practices and their expectations of LA. In the  
4 conclusion, we outline the problems to address when implementing LA as a means to create a  
5 more inclusive and equitable learning environment in higher education.  
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### 9 **Agency and transparency in the context of learning analytics**

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#### 14 *Education in a data-led society*

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19 Much has been written about the role of data and algorithms in society, and several perspectives  
20 from diverse theoretical orientations are now available (Hallinan and Striphas 2016; Kelling et  
21 al. 2009; Kitchin 2014; Turow, McGuigan, and Maris 2015). The ongoing multidisciplinary  
22 debate is concerned with the extent to which Big Data enables novel ways of understanding the  
23 world and acting upon it. Drawing on the literature, Kitchin (2014) argues that Big Data are  
24 often defined as huge in volume, high in velocity, diverse in variety, exhaustive in scope,  
25 striving to capture entire populations (N=all), relational in nature, flexible and scalable. Big  
26 Data is therefore qualified using attributes evoking power and comprehensiveness, but also  
27 heterogeneity and uncertainty. As Kitchin notes (2014, 2):  
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35 The challenge of analysing Big Data is coping with abundance, exhaustivity and  
36 variety, timeliness and dynamism, messiness and uncertainty, high relationality, and  
37 the fact that much of what is generated has no specific question in mind or is a by-  
38 product of another activity.  
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43 This has led to an assertive, optimistic form of empiricism underpinned by a presumed ability of  
44 analytical approaches to generate new insights from Big Data that partial, sampled datasets  
45 cannot guarantee. Indeed, this was the spur behind several forms of data analytics in specific  
46 domains, with LA being no exception.  
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51 In particular, LA has emerged as a solution to address prevalent challenges in education, such as  
52 student retention, widening access, and personalised support for a massive student cohort  
53 (Ferguson 2012; EDUCAUSE 2018). The two main aims of LA are the diagnosis and prediction  
54 of various dimensions of educational performance, both geared towards the production of  
55 'actionable insights' of immediate and demonstrable instructional effectiveness (Clow 2013;  
56 Siemens 2013). Other popular trends include using LA to provide personalised feedback at scale  
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3 (Pardo et al. 2019) and to identify variables and behaviours that promote student success and  
4 address the need for quality assurance of educational services (Lester et al. 2018). Theoretically,  
5 the field of LA is broadly aligned with scholarship in the learning sciences, assessment and  
6 instructional design – while simultaneously positioning itself as a collection of computational  
7 innovations (mostly from data science), made possible by the growing penetration and ubiquity  
8 of digital platforms and devices in education. Similar to themes in the Big Data discourse, LA is  
9 susceptible to the enduringly partial nature of whole datasets, which remain shaped by the  
10 contingent sociotechnical conditions in which they are generated, the dependence on using  
11 technologies for measurement, storage and digitisation, as well as the contextual and domain-  
12 specific assumptions that underpin the deployment of computational methods (Kitchin 2014).  
13 These constraints impose questions on the degree to which learning analytics can present  
14 faithful and fair information about learners in different disciplines and from different socio-  
15 cultural and economic backgrounds.

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17 In the context of education, equity has two dimensions. The first is fairness, which  
18 ensures opportunities to achieve personal potential without being impeded by personal  
19 conditions. The second is inclusion, which ensures a basic minimum standard of education for  
20 all (Simon, Kuczera, and Pont 2007). Similar themes have been highlighted in some LA circles,  
21 with several authors expressing concerns about the unfair differential impact of predictive  
22 models in education (Prinsloo and Slade 2014; Roberts, Chang, and Gibson 2017). This interest  
23 in the fairness of LA is, of course, a reflection of a broader social and scientific debate about the  
24 dangerous tendency of predictive modelling to reproduce existing biases based on race, gender  
25 and class (Richardson, Schultz, and Crawford 2019). Indeed, predictive fairness is an emerging  
26 area of experimentation in the LA field, with new promising techniques such as ‘slicing  
27 analysis’ (Gardner, Brooks, and Baker 2019) being proposed. Slicing analysis evaluates model  
28 accuracy for different sub-groups or individuals to identify unfair differences, which can be  
29 used to identify fairer model. However, questions remain about the tendency to treat fairness  
30 and justice as properties of computational models, rather than properties of social systems  
31 (Selbst et al. 2019). This means that, for example, innovations to make analytics-based  
32 predictions in a MOOC ‘fairer’ might miss the point if they fail to acknowledge the broader  
33 conditions that make MOOC participation more likely among specific gender or race groups.

### 51 52 *Agency and data in education*

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57 The pervasiveness of digital technology has inspired a public debate about fundamental aspects  
58 of human nature (Castañeda and Selwyn 2018). Critical arguments within and beyond academia  
59 often take aim at data-based surveillance, algorithmic manipulation of behaviours and artificial  
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3 intelligence to ask rather philosophical questions about what it means to be human, or to have  
4 'agency'. While an in-depth examination of this topic is beyond the scope of our article, it is  
5 important to identify some key ideas that have particular relevance to the present study, i.e. how  
6 human agency is constrained by digitisation and automation.  
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11 In research that focuses on formal educational settings, i.e. schools and higher education,  
12 agency is generally understood as cognitive and metacognitive agency: a collection of active  
13 processes of knowledge acquisition or development, as well as the complex assortment of  
14 individual strategies that allow awareness of and control over those processes. A number of  
15 studies in the learning sciences and psychology have explored various aspects of agency in  
16 relation to human cognition (computational aspects, situatedness, schemata, motivations,  
17 dispositions and so forth) from a relatively individualistic point of view (Nicholls 1984; Dweck  
18 2000). In education, this is translated into an emphasis on students as rational agents with the  
19 potential to take responsibility for their own learning (Crick and Goldspink 2014). This has had  
20 a notable influence on the development of LA as a distinct discipline (Shum and Crick 2012).  
21 Indeed, aspects of individual cognition have been computationally modelled and then used for  
22 the development of various forms of adaptive or AI-enabled instruction, including various  
23 flavours of 'personalised learning', such as intelligent tutoring systems (providing instructional  
24 advice on a one-to-one basis, akin to human tutors), recommender systems (predicting a user's  
25 preference or needs for an item), and pedagogical agents (simulated figures designed to  
26 facilitate interactions between learners and the computer programme). The individualistic slant  
27 of a large part of research in the learning sciences (and by extension in LA) reflects traditional  
28 empirical foci in psychology.  
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41 By contrast, sociological perspectives tend to favour a different view where human agency is  
42 profoundly shaped by structural factors. In the broader context of digital innovation and the so-  
43 called 'datafication' trend, these sociological perspectives have produced a number of critical  
44 arguments, several of which attend to educational technology and LA in particular. An  
45 increasingly vocal debate within this 'camp' discusses agency in algorithmic 'systems of  
46 control' (Agre 1994; Kitchin and Dodge 2012; Williamson 2015); that is, systems where  
47 computational power is a tool in the service of a pervasive culture of governance that seeks to  
48 exert control through economic rationality, efficiency and individual accountability. This  
49 culture is seen as the result of global factors and influences, which contributed to derail the  
50 process of digital innovation away from the emancipation and the empowerment of human  
51 agency, and towards compliance, control and, often, outright surveillance. In the context of LA,  
52 these arguments have translated into a critique of key notions such as 'actionable intelligence'  
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3 as the focus of LA has shifted, according to some (e.g. Knox 2017), from hindsight to foresight  
4 and prediction. The emphasis on action informed by predictive models has, for its critics, a  
5 tendency to prioritise effects and indicators (signals) over causes, thus leading to narrow  
6 remedial strategies in which students and teachers are channelled along predefined trajectories  
7 of educational performance that, paradoxically, leave little room for agency.  
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### 11 12 ***Transparency and data in education*** 13 14 15 16

17 Transparency is a major theme in current discussions about algorithmic accountability (e.g.  
18 Ananny and Crawford 2018; Tsai and Gašević 2017). This debate has important implications  
19 for LA. Indeed, transparency is one of the overarching goals of the LA project, which seeks to  
20 make learning visible and measurable in order to inform actionable feedback. The transparency  
21 theme is somewhat reversed in critical arguments while retaining the theme of empowerment  
22 through openness. Here, the emphasis is on the need to make computational systems more  
23 accountable in relation to the collection and manipulation of personal data: black boxes to be  
24 opened up and critically interrogated (Pasquale 2015). In both cases, the underlying assumption  
25 is that positive outcomes (evidence-based learning and democratic accountability) will be  
26 attained by rendering complex realities more transparent.  
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34 Transparency and accountability are treated as preconditions for the production of authenticity:  
35 authentic learning, or authentic democratic accountability. This approach may lead to a number  
36 of issues, including what Ananny and Crawford (2018, 7) call a 'false binary' between complete  
37 secrecy and total openness. On the one side, complete secrecy is not only unattainable, but  
38 problematic in its own right in several institutional settings, including education; on the other,  
39 total openness mistakenly assumes that individuals are informed, rational agents perfectly  
40 positioned to maximise benefits from publicly available information. As such, the rhetoric of  
41 transparency in all its manifestations – i.e. as the desirable outcome of analytics or as an ethical  
42 imperative for algorithmic methods – may privilege 'seeing over understanding' (*ibid.*, 8). It  
43 could be argued that the prioritisation of transparency as visibility over self-reflexive knowledge  
44 also underpins the current political discourse of institutional disclosure. For example, the new  
45 European General Data Protection Regulation (The European Parliament and the Council of the  
46 European Union 2016) intends to empower individuals with the right and responsibility to make  
47 decisions regarding the use of their personal data, while institutions are held accountable for  
48 ensuring the transparent provision of relevant information to enable this process. However, the  
49 inherent imbalance in the power relationships in the various contexts in which data is collected  
50 poses questions about the extent to which individuals can truly make informed decisions about  
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3 the use of their data. The implementation of student-centred learning analytics is no exception  
4 (Knox 2017).  
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## 8 **Methodology**

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10 This study sets out to understand teachers' and students' expectations of LA, and questions the  
11 extent to which LA can empower learners and enhance equity in education, so as to move  
12 towards a deliberative, democratic integration of LA. A focus group was chosen to capture data,  
13 taking advantage of dynamics in a group where participants inspire one another and probe ideas  
14 among themselves (Liamputtong 2011) to increase data richness. In particular, focus groups  
15 allow for shared experiences among the participants that increases willingness to discuss  
16 personal views.  
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## 23 **Participants**

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28 To enable in-depth discussions, a focus group typically involves a relatively small number of  
29 participants ranging from four to twelve (Liamputtong 2011). This study involved six student  
30 focus groups, each comprising four to five participants. Participants were invited widely from a  
31 comprehensive university in the UK to include a diversity of student bodies from different  
32 disciplines and degree types. We received 139 positive responses from students, and we selected  
33 six students for each group (6 groups) to represent as many different disciplines as possible. The  
34 selection process was first-come-first-serve, with the constraint that, where possible,  
35 participants were chosen from differing disciplines. However, only 26 students (7 males, 19  
36 females) participated in this case study at the end due to late withdrawals or absence. The six  
37 groups are labelled as UG1, UG2, UG3, UG4, PG, and ODL in this paper. UG1 and UG2  
38 comprise undergraduate students from the Arts, Humanities, and Social Sciences College,  
39 which had the largest student body compared to the other colleges. UG3 comprise  
40 undergraduate students from the Science and Engineering College, and UG4 from the Medicine  
41 and Veterinary Medicine College. PG includes postgraduate students from mixed disciplines  
42 and ODL consists of online-distance learning students from mixed disciplines. Only one  
43 participant from the ODL group had past experience with learning analytics.  
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55 The process of sampling for teaching staff focus groups proved challenging partly due to their  
56 busy work schedules. Five focus groups of participants were sampled widely from the three  
57 university colleges mentioned above (labelled as G1 to G5 in this paper). Twenty-five teaching  
58 staff volunteered but only eighteen (10 males, 8 females) managed to attend the focus groups.  
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3 As a result, three of the groups comprised three to five participants respectively, and two  
4 comprised only two participants due to late withdrawals or absence. Five of the participants had  
5 director roles (e.g., programme director or director of undergraduate studies), and three had  
6 personal tutor roles. Not all the participants had experience with LA, although most of them had  
7 a certain degree of experience of working with or using data to inform their teaching practices.  
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### 11 12 *Procedure*

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17 The focus group interviews were semi-structured, each lasting approximately an hour. All  
18 participants received a short introduction to the concept of learning analytics before the focus  
19 group interviews started. As the institution's adoption of learning analytics was at a rather early  
20 stage, the focus groups were intended to understand participants' awareness and attitudes  
21 regarding existing data practices, which the interviewer drew upon to guide participants to  
22 consider the potential benefits and challenges of using student data for learning analytics. To  
23 this end, ten different questions were designed for staff and student focus groups respectively to  
24 understand their current experience with existing data practices at the university and  
25 expectations or desires to address learning and teaching challenges through LA (accessible here:  
26 [http://bit.ly/FG\\_questions](http://bit.ly/FG_questions)). All participants signed a consent form to participate in the study and  
27 agreed to have their conversations recorded. Each student received ten pounds and each  
28 teaching staff member received lunch in gratitude for their time.  
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### 40 *A thematic analysis*

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44 The focus group interviews were transcribed verbatim and then analysed using a thematic  
45 coding method (Grbich 2012). The coding scheme was developed inductively, which involved  
46 the researcher reading the transcripts repeatedly to identify recurring themes and types of issues  
47 raised. The qualitative analysis tool – Nvivo – was employed to assist in this process. In total,  
48 64 codes categorised into 3 main themes and 14 sub themes were developed to analyse student  
49 focus groups (accessible here: [http://bit.ly/students\\_coding](http://bit.ly/students_coding)), while 59 codes categorised into 4  
50 main themes and 26 sub themes were developed to analyse staff focus groups (accessible here:  
51 [http://bit.ly/staff\\_coding](http://bit.ly/staff_coding)).  
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58 In the following sections, the student participants are denoted as S (student) and teacher  
59 participants as T (teachers) with numbers (1 to 5) to differentiate between individuals in the  
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3 same group. Some of the participants were second language speakers of English. The selected  
4 excerpts are faithful to the original responses, with the minor exception that some redundant  
5 words, such as ‘like’ and ‘you know’, were edited out whenever these words were not  
6 considered to contribute significant meaning.  
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## 10 **Results and discussion**

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16 Our engagement with teaching staff and students highlighted the existence of different  
17 perspectives regarding the role of LA in enhancing equity, agency and transparency, with some  
18 notable misalignments in expectations. These differences need to be considered carefully when  
19 higher education institutions deploy LA so as to cultivate a sense of ownership. In this section,  
20 we present the results in accordance with the two research questions introduced previously.  
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### 24 ***How might personalised data technologies enhance or hamper equity and agency?***

#### 25 *Personalisation and equity*

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31 Learning analytics promises to tailor support to individuals by profiling students using their  
32 learning data and demographic characteristics so as to devise a suitable intervention. In this  
33 way, learning analytics strives to help individuals achieve their optimal potential rather than  
34 bringing every student to the same level of performance. This personalised approach  
35 demonstrates potential in enhancing equity by acknowledging that education is by no means  
36 one-size-fits-all and students at different learning stages require different levels of support.  
37 However, targeted support arguably risks labelling certain groups of students while seemingly  
38 disadvantaging other students by directing resources away from them. We highlighted in our  
39 literature review that fairness and equity are emerging as important concerns in LA, but caution  
40 is needed when treating these dimensions as properties of models rather than properties of social  
41 systems. Our qualitative data extends this point further, providing an insight into the contextual  
42 and personal factors that a ‘diverse’ approach to LA could engage with. For example, some  
43 student participants suggested that LA should help instructors and programme directors  
44 understand the educational backgrounds and learning needs of different students, so as to  
45 provide relevant support instead of overloading students with superfluous information:  
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57 I have ASD [autism spectrum disorder] which causes me social and communication  
58 issues and I’ve sort of spent the first year and a half being quite lonely and isolated at  
59 University and yet overwhelmed by lots of information, but unable to sift through it  
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3 [information bundled up in a generic information] and work out exactly what was of  
4 benefit specifically to me (S4, UG1).  
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8 If English is not your first language, they could use that and make you aware of the  
9 support that is available to you as a foreign language speaker. Now there were some  
10 people who were from very unprivileged backgrounds or people who lived at home  
11 and didn't live at a university accommodation. For them you could be giving more  
12 guidance of how to get involved. So just looking at your background and sending an  
13 email to the people saying, 'Look, this is available'. (S3, UG1)  
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19 While the students generally believed that a personalised approach to educational offerings and  
20 learning support can enhance their educational achievement, some students pointed out the  
21 problem of unfairness when restricting access to resources under the banner of personalisation:  
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25 For the personalisation of services, I wouldn't go so far, because we want to have  
26 equal access to all the services at the university. I would give them data about my high  
27 school years or what curriculum I studied to assess whether all students are on the  
28 same starting level, maybe the beginning of university. And for those purposes to sort  
29 of tailor initial support services (S3, UG2).  
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35 Similarly, the teaching staff expressed a desire to understand the nature of the student body and  
36 relationships between learning behaviour and performance, so as improve the planning and  
37 delivery of a course according to the needs of a growing population of students from diverse  
38 cultural and educational backgrounds:  
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42 I think that sometimes these processes of using data and things like that can help us  
43 with this [widening access]. You know, they can help us to understand the nature of  
44 our student body more effectively and try to tune the ways that we work with them  
45 more effectively (T3, G3).  
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50 However, they were also concerned about 'fairness' in targeted support and the pedagogical  
51 effectiveness:  
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55 I suppose there could be an argument for equity of treatment. You're taking a  
56 particular class of students and you're putting much more effort into them than the  
57 rest. We can sort of say that part of education is being given the freedom to fail on  
58 your own, as opposed to school, you sort of learn from that (T4, G2).  
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5 Despite the common interest among students and teaching staff in using LA to improve  
6 curriculum design and student support, teaching staff tended to look for the big picture of a  
7 student cohort whereas students focused on the differences between individuals and expected  
8 educational equity to be achieved by optimising everyone's opportunity to excel. Nevertheless,  
9 fairness emerges as a central concern around personalisation for both students and teachers.  
10 Moreover, it poses a paradoxical question concerning whether personalisation enhances one's  
11 opportunity to succeed or takes away the opportunity to learn from failures.  
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### 17 *Personalisation and agency*

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22 Agency is the capacity of individuals to 'control' and 'compose' their behaviour for a  
23 determined end, and to anticipate how others would interpret their behaviour (Enfield and  
24 Kockelman 2017). In the context of education, agency is characterised by choice-making in  
25 learning; generating new knowledge; taking responsibility for learning; and engaging in  
26 learning relationships (Crick and Goldspink 2014). LA aims to promote student agency by  
27 positioning students as active actors to make data-informed decisions related to learning  
28 (Kurilovas, Krikun, and Melesko 2016; Mouri et al. 2016; Charleer et al. 2018), such as  
29 adjusting learning strategies upon critical reflections of their behavioural patterns or  
30 performance. However, the range and amount of data that can be collected for learning analytics  
31 to identify suitable support for individuals has often led to ethical issues around surveillance and  
32 'datafying' students (Zuboff 2015). In the focus groups, students, while agreeing that learning  
33 was their own responsibility, expected personalised feedback to guide them in making learning-  
34 or career-related choices. In contrast, teaching staff highlighted a concern about suppressing  
35 learner autonomy through excessive support.  
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45 For example, the students pointed out that information about their learning progress could help  
46 them spend time more efficiently by focusing on areas that need to be improved or working  
47 strategically towards the next assignment or exam. This was perceived as especially beneficial  
48 in the early years of higher education when students are still trying to adapt to a learning mode  
49 that involves fewer interactions with instructors, but more independent effort on the learner's  
50 side.  
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57 Ultimately it is, it's our responsibility. We're adults. We're in control of our own  
58 learning but that doesn't mean that support and guidance and help and pastoral care  
59 aren't still important especially in the first few years (S4, UG1).  
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5 Another student pointed out the struggle when being encouraged to explore ‘whatever they want  
6 to do’:  
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10 Sometimes freedom just makes you lost.... I think what is more helpful is they  
11 [instructors] really show us the optimum way to get to our career rather than let us do  
12 whatever we want, ‘cause they know how we’ve been performing all these years, all  
13 these semesters, and they can see what is our opportunities (sic) in certain areas (S1,  
14 CAHSS2).  
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19 To the students, personalised support and guidance can scaffold the process of exerting agency  
20 on one’s own learning decisions. They objected to the idea of framing education as a self-  
21 centred endeavour, as technology-based learning has increasingly been positioned as  
22 (hyper)individualised or less collective (Castañeda and Selwyn 2018). Similarly, the teaching  
23 staff being interviewed agreed that LA has the potential to enhance student agency with  
24 appropriate support to help them understand and interpret data, thereby leading to self-initiated  
25 changes in behaviours. However, several participants also raised concerns that learning  
26 analytics could potentially hamper rather than enhance student agency:  
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33 The more we start identifying individual students, ‘well, you need a remedial class  
34 because you’re underperforming’, you’re kind of taking that agency away from  
35 students. And I think there is a very big danger of this kind of approach.... Spoon  
36 feeding students, telling them what they have to know, giving them sort of tests and  
37 stuff, has been the way that universities responded to poor satisfaction scores, poor  
38 teaching scores, or whatever it is. In other words, instead of saying ‘students, listen,  
39 we need a dialogue about this’, it’s been more prescriptive action (T4, G3).  
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46 The one thing that we must get over to our students is the primary responsibility for  
47 their learning is there. That really is the bottom line. I mean that’s what you do when  
48 you leave [the university].... What you’re telling the employer [is] this person can cut  
49 the mustard (T2, G2).  
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54 A comparison of the responses from the students and staff reveals mismatched interests among  
55 the key stakeholders of LA. Students tended to focus on addressing their current struggles,  
56 while institutions focused on responding, perhaps in a rather haphazard manner, to the results of  
57 student satisfaction surveys. By contrast, the teaching staff were more concerned that  
58 unbalanced (constant, excessive, or dictating) personalised interventions can have negative  
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3 impacts on the development of a student's problem-solving abilities, which is sometimes gained  
4 through a painful learning process. It was notable that the students emphasised the need for  
5 personalised support to enhance *choice-making in learning* (Crick and Goldspink 2014),  
6 whereas the teaching staff were more concerned with helping students to develop a sense of  
7 *responsibility for learning* (*ibid.*).  
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11 Some teaching staff pointed out the paradox of LA in promoting student agency with  
12 targeted support and meanwhile diminishing it through constant surveillance in online learning  
13 environments:  
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17 There is a series of parallel demands that actually play against one another: being  
18 more independent, having more freedom, and they are being monitored much more  
19 closely... (T2, G4).  
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23 Moreover, the issue of surveillance in creating a sense of remoteness and distance between data  
24 subjects and the data collector (Bauman and Lyon 2012) has also led to discussion on 'being  
25 treated as numbers' among the student focus groups:  
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30 See that this person is beyond just data.... not reducing a person just to the figures  
31 that are being shown on your laptop regarding the person's performance.... You have  
32 to understand why the numbers are coming.... I feel like interaction is the key...to  
33 understand the data you need to understand where it's coming from (S4, UG2).  
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38 Aligned with the students' views, several teaching staff highlighted the risk of removing human  
39 factors by discounting the professional knowledge of teachers or decontextualizing data that are  
40 produced by students who each have different personal circumstances and learning approaches:  
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44 I don't want it [LA] to make all of the students behave in the exact same way to satisfy  
45 an algorithm. I want it to enable students to have the best experience in whatever that  
46 experience is. You know, you can be totally different from everyone else and still do  
47 perfectly fine. I want it [LA] to...enable students to do better and not make them all  
48 mini 'me's (T2, G5).  
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53 Here, we observed resistance to the algorithmic control that has been pervasively used to  
54 enhance economic efficiency in educational contexts (Williamson, 2015), and a call to reflect on  
55 how technologies mould people's emotional and cognitive interactions with each other and with  
56 the machine (Castañeda and Selwyn 2018).  
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3 ***How might existing and expected transparency of data practices strengthen or***  
4 ***compromise student agency?***  
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9 Although the students being interviewed were generally aware that the institution collected and  
10 used certain types of data about them, such as academic and immigration and study permit data,  
11 it was not clear to them who could access the data and how it could be used to improve  
12 academic offerings and support. In general, a phenomenon of information asymmetry was  
13 observed, which arguably diminishes student agency in giving informed consent about the use  
14 of their data. Firstly, the implications of consent given to have one's data collected were not  
15 clear to students at the time of enrolment:  
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22 You have to agree to share this data otherwise you wouldn't enrol, so you are not  
23 probably thinking that much about the consequences of every single piece of data that  
24 you provide to the university. It's just because it's a part of the [application] process  
25 (S4, UG3).  
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30 I've only just sort of begun my studies so I don't think I have enough time in to say  
31 'well, I don't think you should have collected that' (S1, ODL).  
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35 I would assume that [I gave consent at enrolment]. I think often you're signing  
36 consent for things you don't realise.... (S2, PG)  
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40 Although the phenomenon of exchanging data for education is likely to have changed since the  
41 implementation of 2016/679 GDPR (The European Parliament and the Council of the European  
42 Union 2016) in May 2018, the 'lawfulness of processing' in GDPR still allows institutions to  
43 process personal data when it is necessary for the purpose of 'legitimate interests' or to carry out  
44 tasks that are of 'public interest'. Moreover, although these students were explicitly asked to  
45 provide consent, the priority to complete the enrolment process at the moment they came to the  
46 university was likely to cloud their risk assessment on data sharing, or to lead to indifference in  
47 the consequences of sharing personal data. As a result, students compromised on consent-giving  
48 out of *rational ignorance* – users consider the effort and loss of time in reading a lengthy and  
49 complex policy to outweigh the perceived risk of disclosing personal information (Acquisti and  
50 Grossklags 2007). Our analysis provides some evidence in support of contributions that critique  
51 notions of 'ideal' transparency, which places the burden to seek out information about a system  
52 on individuals, and reinforces the mistaken assumption that people will hold perfect information  
53 to make rational decisions and give fully informed consent (Ananny and Crawford 2018).  
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5 Secondly, there has been insufficient communication between the institution and students  
6 regarding what happens after data is collected. The involvement of students often ceases after  
7 their data has been collected. This results in limited understanding of the benefits of opting into  
8 data collection, especially when it comes to giving feedback to improve teaching and  
9 educational services in general:  
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14 Sometimes it just feels like they kind of have to take feedback at the end of the  
15 courses just because it looks nice, but you don't really know if they actually even read  
16 it or use it (S3, UG3).  
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20 It is always like individual feedbacks between us and the university and then we don't  
21 know what the university do, and the university decides by themselves. We are being  
22 separated (S1, UG2).  
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27 This indicates that when opt-in or opt-out options are made available to students sharing data in  
28 exchange for particular LA services or interventions, concrete examples showing how the loop  
29 from data collection to action is closed are crucial to informed consent. This also applies to  
30 cases where service providers are involved, as the students in general showed distrust in sharing  
31 data externally for the fear of becoming the targets of commercial advertisements.  
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36 Thirdly, cognitive limitations in understanding the algorithms embedded in LA systems could  
37 compromise the rational choices in sharing personal data, known as the phenomenon of  
38 *bounded rationality* – self-disclosure decisions are not always rational due to perceived or actual  
39 cognitive limitations in understanding all necessary information required to give informed  
40 consent (Acquisti and Grossklags 2007). In some cases, the opaqueness of algorithms results in  
41 distrust of analytics. This point in particular was raised by teaching staff:  
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47 The cleverer the algorithm, the opaquer and therefore the more dangerous it is.... We  
48 don't know what biases are actually built into the data because the way in which the  
49 data are gathered are contaminated by, for example, issues of race and gender and so  
50 on. So it doesn't take long before an algorithm becomes magic. It becomes something  
51 beyond our understanding and that's dangerous (T1, G5).  
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57 We're kind of caught between two competing demands from the same group  
58 [students], which is on the one hand the demand for more transparency and more  
59 information, and on the other hand, the fact that oftentimes the outcome of that is not  
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3 in any explicable or direct way correlated to the results or what they're doing in the  
4 course. And it actually produces an effect that we don't realise and they don't realise  
5 as well (T1, G4).  
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9 In this case, information asymmetry results from a power imbalance caused by humans making  
10 decisions based on second-hand information (selective summary statistics provided by  
11 algorithms). The complexity of a technological system poses another limitation of transparency;  
12 that is, seeing does not necessarily lead to understanding (Ananny and Crawford 2018).  
13 Moreover, the opaqueness of algorithms can dangerously direct attention away from the process  
14 of learning activities and the associated social, cultural, and political factors in the broader  
15 context. As a result, it becomes an almost impossible task for students to challenge the precision  
16 of analytics of their learning.  
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## 22 23 **Conclusion**

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25 Our analyses have identified conflicting interests in LA among students, teachers, and  
26 institutions, which have led to mismatched perceptions and expectations about the way LA can  
27 be used to enhance learner agency and improve equity. We argue that LA-based interventions  
28 should not be assumed to empower students. A number of intertwined factors have contributed  
29 to the tensions between enhancing a learner's control of their studies and, at the same time,  
30 diminishing their autonomy as an active agent in the process of LA. These factors include the  
31 way interventions are devised and delivered, the way data is collected, analysed, and  
32 interpreted, the transparency of the data process, and the opaqueness of algorithms. We  
33 summarise our findings with three recommendations to mitigate the observed tensions:  
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43 First, interventions need to be based on the learning sciences to balance what students want and  
44 what is good for them. It is notable that students are concerned about making good  
45 decisions regarding learning and career development, whereas teachers highlighted the  
46 risks of learning analytics in terms of spoon-feeding students, leading to the removal of  
47 agency. While these two views do not necessarily conflict with each other, they  
48 highlight the importance of devising LA-triggered interventions based on learning  
49 sciences. For example, the seven principles of feedback proposed by Nicol and  
50 Macfarlane-Dick (2006) could be used as a framework for LA-based feedback to drive  
51 self-regulation.  
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Secondly, LA needs to leverage rather than replace human contact. Key to this is a realistic

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3 evaluation of staff capacity and capability to deliver interventions. While the students generally  
4 bought into the rhetoric of personalisation advanced by learning analytics, their idea of  
5 personalisation was not necessarily a computational one. In fact, they lamented the lack of  
6 individualised support from human tutors, while showing a degree of suspicion for automated  
7 systems that focus on coarse, dichotomous metrics of educational performance, such as the risk  
8 of dropping out or failure. On the one hand, this suggests a desire to maintain a degree of  
9 control, indeed agency, over learning; on the other, it points to a notion of support that is  
10 dialogic, human-based and, inevitably, labour intensive in nature. Mirroring these concerns,  
11 teachers pointed to the confusion between individualised support and ‘industrial-scale  
12 provision’ – a confusion that has been introduced by the institution as a result of pressures to  
13 widen access to higher education as well as demonstrate performance via quantitative  
14 indicators, such as student satisfaction and progression. As a result, the version of  
15 personalisation expected by students was considered unrealistic by teaching staff, in that such  
16 levels of support cannot be delivered by humans without placing undue pressures on already  
17 heavy workloads.  
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29 Thirdly, issues of transparency and visibility in terms of data policies, practices, and algorithms,  
30 requires a more informed debate around the implications for agency. An important question, in  
31 this regard, is the following: to what degree does agency depend on a relative lack of visibility  
32 and transparency? Despite the fact that obtaining explicit consent before data is collected and  
33 processed has been acknowledged as a requirement in Europe, the ineffective communication of  
34 policies puts burden on students seeking to comprehend the consequences of giving data away  
35 and being responsible for it. This appears like an effort to fulfil an obligation rather than to help  
36 students develop agency in any constructive way. Moreover, the disengagement of students in  
37 phases beyond data collection and the challenge of making algorithms transparent in a  
38 comprehensible way discredit the idea that LA empowers students, as little room has been left  
39 for agency in this remedial approach.  
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48 The paradox of agency highlights the need to ‘deobfuscate’ the politics of data-based  
49 personalisation. Indeed, this is not only an ethical priority but also a methodological one,  
50 concerned with a more accurate understanding and communication of the inner ‘sociality’ of  
51 algorithmic diagnosis and prediction. It is crucially important to acknowledge and address the  
52 conflicting beliefs about data-based personalisation, surveillance, and agency when introducing  
53 LA as an equitable solution to educational challenges. In order to mitigate these conflicts,  
54 institutions need to intentionally involve different groups of users in a partnership to design and  
55 implement LA (Dollinger and Lodge 2018; Roberts, Chang, and Gibson 2017), and develop a  
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context-based policy (Tsai, Moreno-Marcos, Tammets, et al. 2018) that ensures the deployment of LA to align with the institutional values of inclusion, equity, and student autonomy.

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