Effective usage of Learning Analytics: What do practitioners want and where should distance learning institutions be going?

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The implementation of learning analytics may empower distance learning institutions to provide real-time feedback to students and teachers. Given the leading role of the Open University UK (OU) in research and application of learning analytics, this study aims to share the lessons learned from the experiences of 42 participants from a range of faculty, academic and professional positions, and expertise with learning analytics. Furthermore, we explored where distance learning institutions should be going next in terms of learning analytics adoption.

The findings from the Learning Analytics User Stories (LAUS) workshop indicated that four key areas where more work is needed: communication, personalisation, integrated design, and development of an evidence-base. The workshop outputs signalled the aspiration for an integrated analytics system transcending the entire student experience, from initial student inquiry right through to qualification completion and into life-long learning. We hope that our study will spark discussion on whether (or not) distance learning institutions should pursue the dream of an integrated, personalised, and evidence-based learning analytics system that clearly communicates useful feedback to staff and students, or whether this will become an Orwellian nightmare.

Keywords: Learning Analytics, Distance learning, Expert discussion.

Introduction

Across the globe distance learning institutions are exploring the opportunities technology affords to provide a better, more consistent, and more personalised service to their students and stakeholders (Eom & Ashill, 2016; Gelan et al., 2018; Herodotou et al., 2017; Rienties & Toetenel, 2016; Tait, 2018). In particular, the development of learning analytics (Agudo-Peregrina, Iglesias-Pradas, Conde-González, & Hernández-García, 2014; Colvin et al., 2015; Daniel, 2015; Ferguson et al., 2016; Macfadyen & Dawson, 2010; Tempelaar, Rienties, & Giesbers, 2015) may empower distance learning institutions to provide near real-time actionable feedback to teachers and students about what the "best" next step in their learning journeys might be. For example, several distance learning institutions have started to explore the use of learning analytics dashboards that can display learner and learning behaviour to teachers and instructional designers in order to provide more real-time or just-in-time support for students. (Herodotou et al., 2017; Jivet, Scheffel, Specht, & Drachsler, 2018). Furthermore, several distance learning institutions have developed predictive learning analytics approaches to help identify, as early as possible, students who may be considered 'at risk' of failing, and which of those students may need additional support (Calvert, 2014; Herodotou et al., 2017; Wolff, Zdrahal, Nikolov, & Pantucek, 2013). Some institutions are also currently experimenting with providing learning analytics data directly to students in order to support their learning processes and self-regulation (Rienties, Tempelaar, Nguyen, & Littlejohn, Forthcoming; Winne, 2017).

As evidenced by several reviews and policy documents (e.g., Ferguson & Clow, 2017; Higher Education Commission, 2016; Hoel, Griffiths, & Chen, 2017; Raths, 2016), one of the front-runners in learning analytics in higher education, and distance learning in particular, is the Open University UK (OU). The OU was the first institution to implement an institutional ethics policy in learning analytics (Slade & Boroowa, 2014), has a university-wide implementation of predictive learning analytics for its 170,000+ students (Calvert, 2014; Herodotou et al., 2017; Wolff et al., 2013), and has worked extensively with teachers to use real-time and near real-time data of students to inform their teaching and learning practice (e.g., Hidalgo, 2018; Mittelmeier et al., 2018; Olney, Rienties, & Toetenel, 2018; Rienties, Boroowa, et al., 2016; Rienties, Cross, Marsh, & Ullmann, 2017). Since 2014 there has been a strong strategic drive from OU senior management to use some of the powers of learning analytics to improve the provision of learning and teaching[i], while at the same time there is an increasing groundswell of interest from the "shop floor" by diverse groups of individuals, and semi-organised groups of researchers, instructional designers and academics who are piloting and small projects and initiatives that look to explore how learning analytics could be used on a day-to-day basis.

Like many distance learning institutions, the OU is struggling to compete in an increasingly global and localised market of higher education provision, with reduced central funding from governments (Baker, 2018), and an increasing number of "traditional" universities offering blended and online degrees (Conijn, Snijders, Kleingeld, & Matzat, 2017; Tait, 2018). Learning analytics might provide opportunities for (semi-) automatic personalisation as well as increased flexibility of online provision, while at the same time potentially benefiting from efficiency and retention gains when providing education at scale. Nonetheless, there are several critics towards this learning analytics and data-centred movement (Castañeda & Selwyn, 2018; Weller, Smith, & Brandon, 2018). Some critics tend to focus on the perceived dilution of the role of the human teacher as a provider of the personal support role to (semi-) automated support provisions – even though the primary objective is to improve and extend the interventions teachers already make. Further criticism is directed at the ethical use of student data (Prinsloo & Slade, 2016), see also a recent review on global guidelines on ethics for distance learning institutions by Slade and Tait (2019).

In order to explore to affordances and limitations of learning analytics approaches used at the OU, the authors organised an interactive workshop in September 2017. We were keen to explore the potential next frontiers in learning analytics adaptation in the context of an institutional change programme. 42 participants from a range of faculty, academic and professional positions (including IT and the strategy office), and expertise with learning analytics participated in a four-hour in-depth participatory workshop called the Learning Analytics User Stories workshop (LAUS). The aim of LAUS was to explore the potential of an analytics system across the OU, and to bring together the various researchers, interest-groups and enabling functions to develop a shared understanding of how analytics might benefit the institution, teachers and students. The workshop was designed as an initial foray into what an analytics system might resemble in practice, drawing on the lessons learned from the last four years in terms of learning analytics adoption. Given the leading role of the OU in terms of research and the application of learning analytics, sharing these lessons learned, pitfalls, and the authors' own reflections might help other distance learning institutions to consider how they might respond when faced by the same inevitable challenges. Therefore, two research questions of this study are:

1) What do university staff want in terms of effective usage of learning analytics?
2) Where should distance learning institutions be going next in terms of learning analytics adoption?

Learning analytics at the Open University

Conceptualisation of learning analytics and what works

The OU has been at the forefront of the conceptualisation of learning analytics since its inception in 2011 at the first Learning Analytics Knowledge (LAK) conference in Banff (Long, Siemens, Conole, & Gasevic, 2011)[ii]. For example, Ferguson and Buckingham Shum (2012) proposed a social learning analytics approach that takes into consideration how learners build knowledge together in their cultural and social settings. In addition to building a clearer conceptualisation of the purpose and affordances of learning analytics, the OU has been a strong proponent of providing evidence of "what works" in learning analytics. Building on the European LACE project, several reviews of what works and does not work in learning analytics have been published by the OU (e.g., Ferguson et al., 2016; Ferguson & Clow, 2017). For example, while reviewing 123 case-studies submitted to the LACE evidence hub, 86 studies indicated that the use of learning analytics had a "positive" effect on learning, whereas only 7% of cases were listed as having a negative effect on learning (Ferguson & Clow, 2017). However, as argued by both Rienties, Cross, and Zdrahal (2016) and Ferguson and Clow (2017), few learning analytics studies used robust research design approaches to test whether a particular learning analytics intervention effectively worked or not, given the lack of a comparison or contrast condition and randomisation of treatment.

Ethics

There are several ethical and privacy concerns (e.g., collecting sensitive data, labelling, profiling) when distance learning institutions are starting to use data to profile, predict, and identify particular learning behaviours in order to improve the teaching and learning provision. Therefore, the OU has provided a leading role in the conceptualisation and implementation of ethics and privacy in learning analytics. According to the Higher Education Commission (2016), "The [OU] was the first institution worldwide to develop a policy specifically on the ethical use of learning analytics, published in 2014." The Ethics Policy on Learning Analytics was developed by the OU (Open University UK, 2014; Slade & Boroowa, 2014) after extensive consultation with students, teachers, staff, and legal experts, and have been adopted by a range of institutions across the globe. For example, this policy document has structurally contributed to frame the JISC Ethics policy (Sclater & Bailey, 2015). In a recent review of ethics learning analytics policies across the globe, Hoel et al. (2017, p. 249) argued that the OU "has been a trailblazer in developing institutional policies on ethical use of student data for LA", and a range of institutions have adopted similar ethics policies based upon the work by the OU.

Predictive learning analytics

Without an appropriate, linked IT infrastructure that captures key learning activities of students (and teachers), it would be difficult to implement effective learning analytics in the first place for distance learning institutions. The Higher Education Commission (2016) indicated that "predictive analytics can identify which students may not complete their degree on time or even hand in individual assignments, which is already being seen in the UK through the OU Analyse tool. Apart from the OU the Commission does not believe that any UK institution has made significant headway in this area." Since 2013 the OU has been developing, conceptualising and implementing large-scale predictive learning analytics applications (e.g., Calvert, 2014; Hlosta, Herrmannova, Zdrahal, & Wolff, 2015; Wolff et al., 2013), which has had a large impact both in terms of the conceptualisation and the implementation of learning analytics at other institutions.

At present, one generic predictive learning analytics system originally developed by Calvert (2014) provides "risk-profiling" for all 170,000+ students based upon 30+ indicators at four time points during a module to teachers and support providers. Furthermore, a second more fine-grained predictive learning analytics system called OU Analyse provides weekly predictions and recommender options to hundreds of teachers across 20+ modules that adopted its' use. (Herodotou et al., 2017; Hlosta et al., 2015; Wolff et al., 2013). At present the OU provides data from these two learning analytics systems directly to teachers and support providers. One reason why these data are not provided directly to students is that the OU has one of the highest rates of students with a declared mental illness or physical accessibility needs (Coughlan, Ullmann, & Lister, 2017), and providing direct visual feedback via a computer might not be in the best interest for some groups of OU learners.

Pedagogically informed learning analytics

Since the inception of learning analytics, beyond the cold numbers and algorithms, the OU has continuously stressed and focussed on the benefits of gathering, visualising, and interpreting pedagogically informed learning analytics (Rienties, Cross, et al., 2017). This is exemplified by embedding the findings from the Open University Learning Design Initiative (OULDI) in design approaches, and includes the application of an Activity Types Classification Framework to module curriculum design and implementation across the OU. Conole (2012) described OULDI as "a methodology for enabling teachers/designers to make more informed decisions in how they go about designing learning activities and interventions, which is pedagogically informed and makes effective use of appropriate resources and technologies". This framework has allowed the OU to both conceptualise (Olney et al., 2018; Rienties, Nguyen, Holmes, & Reedy, 2017; Toetenel & Rienties, 2016) and empirically provide support of the importance of adding learning design to predicting student behaviour and outcomes (Nguyen et al., 2017; Rienties & Toetenel, 2016).

For example, in a review of 151 modules at the OU, Rienties and Toetenel (2016) found that the best predictor for student retention was whether teachers included communication learning activities (i.e., student to student, student to teacher, teacher to student) into their learning design. Furthermore, when linking weekly learning analytics data of user engagement of 17,000 students across 38 modules with their specific learning designs, Nguyen et al. (2017) found that 69% of variance in weekly students' behaviour was explained by how teachers designed their modules on a week by week basis. Indeed, Toetenel and Rienties (2016) found that providing direct visualisations of initial learning design decisions by teachers could help them to design more engaging, interactive learning designs. In other words, learning design has a fundamental importance on how students learn, and learning analytics approaches can benefit by incorporating learning design proxies into their algorithms and visualisation. As highlighted elsewhere in this journal (Mittelmeier et al., 2018), there is some evidence to support that the OULDI approach can be transformative to other institutions, such as in Africa, and more recently in China.

Professional development and training of staff

While many studies (e.g., Colvin et al., 2015; Ferguson et al., 2016; Jivet et al., 2018) have indicated the potential of learning analytics tools, engines, and dashboards, the success of the adoption of any learning analytics approach ultimately relies on its endorsement by teachers. Teachers are one of the key stakeholders who will access and interpret learning analytics data, draw conclusions about students' performance, take actions to support students, and improve the design of the curriculum. Distance learning institutions need to empower teachers further by introducing appropriate professional development activities to improve teachers skills in effectively using technology and learning analytics dashboards (Mittelmeier et al., 2018; Rienties, Herodotou, Olney, Schencks, & Boroowa, 2018).

Research and practice (Herodotou et al., 2017; Olney et al., 2018; Rienties & Toetenel, 2016) at the OU has highlighted that although many teachers and instructional designers see the potential benefits of learning analytics, not all teachers actively engage with learning analytics without appropriate professional development, motivation, and support. For example, Herodotou et al. (2017) found that although many teachers used OU Analyse to inform what their students were doing, most teachers only occasionally logged into the system, and at times struggled to provide actionable feedback to students. Similarly, in a professional development training programme of 95 teachers Rienties et al. (2018) found that even though most participants thought that learning analytics dashboards were useful and intuitive, and that the training was effective, many believed that without ongoing and follow-up support they would not be able to incorporate learning analytics dashboards into their own practice.

At present the production system and use of learning analytics at the OU is primarily focussed on single module design, production, and evaluation. Most of the design decisions for OU modules are made in advance, with a relatively long production cycle. Furthermore, the design of modules are often independent from the sequence of modules in a qualification (Rienties, Clow, et al., 2017), and with limited direct insight from actual learning analytics data (Nguyen et al., 2017). In addition to the long production cycle is the complication that most modules are designed for a five to ten-year lifespan, and have limited opportunities to change the design and production based upon new insights and learning analytics. The volume of analytics data also varies across modules. Many introductory modules have one or two predictive learning analytics data feeds, and at various specific points in time modules teachers and support providers get learning analytics predictions of their students (Calvert, 2014; Hlosta et al., 2015). Follow-up and more specialised modules often have fewer data points because of smaller student samples, and therefore offer less fine-grained and predictive learning analytics data.

Beyond module production and implementation, learning analytics are not used at the stage of student inquiry. In addition, except for recommended pathways in a respective qualification by the official study planner for each qualification, the OU at present does not provide learning analytics data to students about which modules would be best for them to follow next, and which combination of modules would be the “most” appropriate to lead to a qualification, which is done elsewhere (Denley, 2014; Phillips, 2013). Finally, no specific learning analytics are in place to help graduates with their lifelong learning options, including follow-up study at the OU or involving graduates into OU education.

The need for an analytics system

While the OU has a rich understanding of learning analytics and an array of successful pilots and integration into certain parts of the curriculum, it is still seeking institution-wide adoption of some proven practice, and is yet to explore many possible interventions. From the OU experience it is clear that effective learning analytics policies, accurate and valid predictive analytics approaches, pedagogically sound learning design principles, and professional development support provide only a foundation for practice. Designing an analytics system requires a shared understanding of the potential for learning analytics, involving multiple perspectives, so that the right data is captured, correctly analysed, conveniently and ethically shared, and appropriately applied. Across these important activities there is a strong need to align key stakeholders (i.e., senior management, teachers, instructional designers, academics, professional support staff) with the potential of learning analytics to effectively implement an analytics system on a large scale. Although learning analytics is used at the OU in some critical areas, there are many more opportunities and possibilities. To explore these, we gathered together decision-makers and experts from across the university. In the remainder of this study we will describe how we designed the LAUS workshop, and critically reflect on our findings.

Methodology

Design and procedure of LAUS workshop

The Learning Analytics User Stories (LAUS) workshop was developed, designed and implemented by three of the four authors within the OU with years of practical and evidence-based workshop training experience to accommodate the range of backgrounds and levels of expertise and seniority present in the key stakeholders. This innovative and interactive workshop was designed to explore what the OU has learned from four years of learning analytics, and how to approach or push the next frontiers of learning analytics.

The LAUS brought together two workshop techniques in an innovative approach designed to achieve the desired outcomes. The participants were randomly seated around six tables in groups of seven, to maximise the diversity of expertise and experience at each table. In this way, if one participant did not know of a particular learning analytics tool or approach, it was expected that some of the peers around the table might provide some advice that was less intrusive than continuously having an instructor "breathing down their neck".

After an initial context and scene setting presentation, Phase 1 was facilitated by the second author who employed the Consensus Workshop methodology (ICA:UK, 2018) to surface ideas from the room about the future for learning analytics at the OU[iii]. This methodology is used increasingly at the OU in different situations and contexts due to its versatility and adaptability. For example, also pioneered its use in learning design workshops to surface key design challenges that academic teams might be facing in the very early stages of module development. Skilled implementation has been found to foster collaborative thinking and, as the name suggests, the ability to reach consensus in a non-confrontational and inclusive manner; crucial to successful curriculum design. Vital to the successful use of this technique is the establishment and articulation of a central question the participants need to answer in order to move ahead. In this case it was collaboratively decided that this question should be, 'In an ideal world, in what possible ways could we use learning analytics at the OU?'

Initially, in line with the Consensus Workshop technique, the participants were asked to spend several minutes listing their individual responses to the central posed question. This first session gives time for a thoughtful, initial gathering of ideas, free from the influence of others. Then, working with a colleague, or in groups of three, they were asked to collaboratively develop a selection of responses that could be written in three to seven words on an A5 piece of paper (referred to as a 'card'). During this activity, the second author circulated the room responding to questions and confirming the process, but importantly not commenting on the content.

Once each pair, or small group, had developed between six to eight 'cards' we collected about half of the most important initial ideas by each group and displayed them on a 'sticky wall' at the front of the room (a 'sticky wall' is a sheet of lightweight poly-canvas, taped to the wall of the room and sprayed with non-permanent adhesive, so that cards can be placed on it, and moved around freely). The second author then facilitated a discussion in the room designed to clarify and elicit meaning from the participants around the cards they had produced and enable the 'clustering' of the cards into thematic groups. After consensus had been reached on the clustering process the remaining cards were gathered from the participants and added to the sticky wall in appropriate clustered groups and labelled. Finally, after the clustering of themes, the workshop participants used them to develop learning analytics user stories in Phase 2 of the workshop. The participants were initially asked, in their table groups to take the consensus possibilities for learning analytics and use them to develop epic stories based upon four user profiles: teachers; students; professional support staff; and management.

One of the advantages of this technique is that it gives an opportunity for the ideas of all participants to be displayed in front of the whole group. Other group facilitation techniques require a much earlier prioritising of ideas, i.e. at table or group level, which means that good ideas can be lost to those of louder or more confident participants. Furthermore, the opportunity for the whole group to consider the validity of any one idea might be missed. Furthermore, using this kinds of user-stories means that the design of the learning analytics system can reach across all three of Daniel (2015)'s essential stages of Big Data. The user-story approach is appropriate given the opportunity to develop a complete analytics system, to the extent that points of data collection can be designed into a new learning analytics approach for distance learning. The purpose of this initial workshop was to gather some high-level ideas to inform further consultation and engagement.

Participants

We aimed for a wide, diverse group of senior managers, teachers, and professional support staff who were responsible in terms of management and vision, and/or used learning analytics approaches and tools as part of their functional role. Email invitations were sent out via a range of channels. 42 participants joined the LAUS workshop, 16 (38%) of whom were women. The average age of participants was 43, with a range of 34 to 62. In total 14 (33%) were from one of the four faculties, mainly from science, education, health-care, and business, and 28 (66%) were from central units, such as IT, student support services, or central academic development. There were 11 academic staff[1] , 31 professional staff[2], and two project assistants. Overall, a wide sample of participants, roles, and levels of experience with learning analytics were present, although associate lecturers and students were not specifically sampled.

Data analysis

As indicated above, all data were constructed jointly on the sticky wall, and afterwards organised by the participants and facilitators. The final 13 themes were clustered by the participants and facilitated by the second author. After the event, all data were transcribed, shared, and discussed between the authors. The third author, who was not part of the actual LAUS Workshop, independently analysed the data as well in order to provide counter perspectives, and to verify the themes. The writing of this study, and in particular the discussion of the various versions of this study was an iterative process.

Results

Phase 1

42 participants worked on their respective tables during the LAUS workshop to discuss the ways forward and how the university might use learning analytics to further benefit OU students. In Table 1 the initial 13 themes from the LAUS workshop are provided. These link together to form four key summary areas: communication, personalisation, integrated design, and development of an evidence-base. The workshop outputs signal the aspiration for an integrated analytics system transcending the entire student experience, from initial student inquiry right through to qualification completion and into life-long learning.

- ➔ Insert Table 1 about here

1) Improved communication supported by learning analytics

In terms of *communication*, participants indicated that there is a need for integrated learning analytics solutions that can support optimised peer to peer support (Table 1, theme 2), whereby it could support effective learning communities and help students to learn from one another. It is widely documented that collaboration and peer-learning are essential drivers and motivators for study success in distance education (Ferguson & Buckingham Shum, 2012; Rienties & Toetenel, 2016). However, most of these formal and informal communication options (e.g., discussion forums, Facebook, WhatsApp) between OU peers happen by chance (e.g., by the

[1] Three (7%) senior academic managers (i.e., Associate Dean, Director), three professors, two senior lecturers, one lecturer, one post-doc, and one PhD student

[2] Four (10%) directors, four heads of unit, 17 (41%) senior managers (e.g., head of student success, senior instructional designer, programme manager) four project or programme managers

group they are randomly enrolled in), rather than informed by a clear institutional or pedagogical strategy with appropriate learning analytics support (e.g., providing level 1 students support by 2nd year students, allocating students into follow-up modules based upon similar working patterns). By providing an integrated learning analytics solution giving students more detailed insights (e.g., what pedagogical approach works for students like them, what their colleagues liked and did not like about Module X and Y, which students have registered for the next advanced Marketing module), students from different modules and qualifications, as well as graduates and alumni could help and support each other.

Another key element of improved communication is to better inform student choice (Theme 7-8), whereby potential students (inquiry/enquiry) are provided with intelligent decision-making tools indicating the best options in reach, and which are available for them. In line with Denley (2014), students might be provided with learning analytics tools that enable decision making about appropriate pathways, and better information about how their goals and mode of study could help them to make an informed choice which pathway(s) might be best for them.

2) Personalisation to recognise unique distance learners' needs

Participants indicated a clear desire for *personalisation* both for teachers and for students. In part this was reflected by a greater need to understand the types of learners that attend distance learning environments (Theme 10), and in part by providing a better understanding of the different profiles of students so that learning analytics could be used to provide potential interventions where needed. For teaching staff, learning analytics could be used to personalise learning support based on well-being, accessibility needs, or additional requirements (Theme 5). Furthermore, analytics could be used to target support to students struggling with concepts and assessment, and to identify and support 'at risk' students by focussing tutorial and support staff. From a student perspective, learning analytics could help to provide personalised feedback on study technique and encourage reflection (Theme 6), such as recently indicated by Fincham, Gasevic, Jovanovic, and Pardo (2018), and to enable students to maximise study time and efficiency. In part this could also be achieved by personalising content for the student, even at sentence level (Theme 7), such as suggested recently (FitzGerald et al., 2017; Gelan et al., 2018; Higher Education Commission, 2016).

3) Integrated design from inquiry to lifelong learning

Participants suggested a clear need identified for a systems approach to integrate learning analytics and design throughout the students' journeys (i.e., Theme 1, 4, 11). For example, several ideas were put forward allowing students and teachers to co-create their learning activities (Theme 11), supported by learning analytics to better integrate design with teaching and learning. In particular, by linking learning design data with what students are doing in terms of assessment, tuition, and behaviour could help to inform how to adjust the learning design for specific groups of learners and learning needs (Mittelmeier et al., 2018; Nguyen et al., 2017; Toetenel & Rienties, 2016). At the same time, the learning designs developed and fine-tuned should be fun and students-led (Theme 1), possibly designed and led by students, graduates, and alumni, rather than a common practice in distance learning and higher education whereby designs are principally determined by academics in long design cycles. Interestingly, learning analytics could also be used to identify "vampire" modules that compete with other modules, rather than drawing in new students (Theme 4).

4) Develop a strong evidence base what works and what does not

Finally, participants wanted to establish a stronger evidence-base for their practice, and in particular also use professional development to become a smarter distance learning environment (Theme 12). As mentioned earlier, even though a large number of distance learning providers are investing heavily into learning analytics, there are still a lot unknown about what works and what does not (Ferguson et al., 2016; Ferguson & Clow, 2017). Furthermore, it is important that the organisation is acting upon learning analytics (Theme 13), and give actionable data both to teachers and to students, in line with Jivet et al. (2018). This evidence could not only inform appropriate interventions with students, but should also inform the design of modules, qualification pathways, and routes to life-long learning.

Phase 2

During the final part of the LAUS workshop, participants worked on potential user stories along four main user groups: students; teachers; professional staff; and management. A range of interesting and innovative ideas were put forward, whereby as a student:

- I want to know that the experience I have had, and previous students, will be used to improve future studies (acting on analytics/co-created).
- I would like to understand my engagement in relation to my cohort so that I can find suitable learning partners.
- I would like to have automated support a) to get quicker feedback about my progress and behaviour and b) so that I can progress at my own pace

In terms of teachers, a generally pro-active approach of using data to improve learning design and support was put forward, such as a teacher:

- I would like to know factors influencing learning so that I can take this into account when designing new curriculum.
- I would like to identify areas of the curriculum that past students have not engaged with so that it can inform an alternative route through the study materials.
- I would like to know if my students are engaged with learning in real-time so I can intervene if necessary.

In terms of professional support staff and senior management, there was a strong emphasis on providing a supportive culture, and making effective use of learning analytics data. For a complete overview of the various user stories, see Appendix Table 1.

Limitations

The LAUS workshop was an initial session with a broad group of OU stakeholders designed to bring together multiple perspectives, in order to develop a systematic view of how learning analytics might be better applied. The number of participants is considered at the upper level for an effective Consensus Workshop, and so further engagement with the multiple and important groups not represented in the LAUS is required. Nonetheless, 42 participants by no measure can represent a complex and dynamic organisation like the OU, and therefore follow-up research is needed within this context and others to determine if our findings are generalizable. The results gave a rich diversity of ideas, which need to be further validated by a greater representation of OU staff and (in particular) students. Participants were encouraged to think as broadly and openly as possible, so next steps will involve further refining the themes toward possible projects. With any qualitative research method there are known issues with self-selection bias, group think, and dominant personalities. However, as participants could share their epic user stories also via email afterwards, and a wide body of participants with familiarity of both learning analytics and their institutional roles participated, these potential biases in part might be mitigated. A final limitation of our work is that we only included perspectives from OU staff members. Future research should explore the perspectives of current and future students, and listen carefully to their perspectives, needs, and potential anxieties.

Conclusion

Building an integrated learning analytics system that works is a dream for many higher educational stakeholders across the globe (Ferguson et al., 2016; Higher Education Commission, 2016; Rienties, Boroowa, et al., 2016), and a potential nightmare for others (Castañeda & Selwyn, 2018; Prinsloo & Slade, 2016; Weller et al., 2018). In this study we explored the experiences with learning analytics and desired future affordances of 42 professional experts and practitioners at one of the largest adopters of learning analytics in Europe, the OU. Our LAUS workshop demonstrated the benefits of bringing together a variety of stakeholders, already informed as to the possibilities of learning analytics, to share possibilities and generate ideas for establishing an analytics system. The event also served to bring together representatives from different parts of a large university, to discuss analytics from a number of different functional perspectives.

In terms of Research Question 1, the thirteen themes emerging from the workshop showed a broad set of considerations, ranging from foundational considerations right through to implementation aspirations. The Consensus Workshop methodology resulted in a shared ownership of the ideas, an agreed position that can be taken forward with confidence as the beginning of an all-of-university plan. For example, some faculties are planning to use the outputs from LAUS to inform, develop and clarify their own learning analytics requirements in 'mini-LAUS' workshops as this piece of work enters a new development phase. The process drew together different assumptions and views of what analytics might achieve, and provided a very rich tapestry of potential much broader than the authors thought would result.

The LAUS is a first-stage in what will necessarily be a much longer journey. As highlighted by a range of studies (Calvert, 2014; Colvin et al., 2015; Daniel, 2015; Ferguson & Clow, 2017), developing an analytics system requires a great deal of design, planning, investment and testing across educational designers, researchers, IT developers, data engineers, business analysts, and teaching & support staff. Extending analytics potential beyond the discreet functions of providing feedback on module performance to teachers (Calvert, 2014; Wolff et al., 2013) and to students (Jivet et al., 2018; Rienties et al., Forthcoming) will take a significant amount of systems thought and cross-departmental coordination.

In terms of Research Question 2, at the very least the four key summary areas of improved communication, personalisation, integrated design, and evidence base will guide the all-of-university future approach to implementation. This will be a massive challenge for any distance learning institutions, including the OU. At the same time, we hope that by sharing of our lessons learned with the wider open and distance learning community that others are inspired to also share their experiences with initial learning analytics implications. Furthermore, we hope that our study will spark discussion on whether (or not) distance learning institutions should pursue the dream of an integrated, personalised, and evidence-based learning analytics system that clearly will communicate useful feedback to staff and students, or whether this will become an Orwellian nightmare...

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Table 1: Themes from LAUS Workshop

Theme 1: Design to make demand (what matters to students).
• Make it fun. • Put students first. • Design it to be student-led, machine assisted.
Theme 2: Link to peers (optimised peer to peer support).
• Consider student behaviours in wider university systems. • Create more effective learning communities. • Help students learn from other students.
Theme 3: "Are you being served?" (real time sensing).
• Measure real-time student engagement, to provide proactive support. • Gather real-time feedback on what works and doesn't for students. • Measure student engagement with specific learning activities.
Theme 4: Curriculum design.
• Inform curriculum design and development. • Identify new curriculum designs/offers. • Identify "vampires" (modules that compete with other modules, rather than drawing in new students).
Theme 5: Personalise 'support to succeed': Tuition and support facing.
• Personalise learning support based on well-being/disabilities/additional requirements. • Target support to students struggling with concepts and assessment. • Identify and support 'at risk' students by focussing tutorial and support staff.
Theme 6: Personalise 'support to succeed': Student facing.
• Give feedback on study technique and encourage reflection. • Enable students to maximise study time and efficiency. • Frequent targeted feedback on progression through learning.
Theme 7: Navigate pathway success.
• Personalise (automate) module/learning/career pathways. • Enable understanding of learning approaches and gains to better guide learning. • Personalise content for the student, at the sentence level.
Theme 8: Inform student choice.
• Provide enquiry stage 'intelligent' decision making tools. • Enable decision making about appropriate learning pathways. • Better advise study goals/mode of study/choices of pathway/modules.
Theme 9: Automate learning support.
• Automate the initial level of support (A.I), 24/7. • Personalise (automated) in-learning marketing. • Provide access to support services through smart home speaker (Alexa, Googlehome).
Theme 10: Provide insight for effective learning intervention.
• Deepen our understanding of our students. • Provide comprehensive profiles. • Establish those factors that influence learning.
Theme 11: Design co-created, evidence-based learning.
• Improve learning design (assessment, tuition, workload) based on behaviour and outcomes. • Establish evidence-based learning design principles. • Enable students to co-create learning resources.
Theme 12: Become a smart university
• Improve our analytical skills and abilities. • Demonstrate the OU as a learning organisation.

• Link analytics to staff professional development.
Theme 13: Acting on analysis
• Enable students to monitor their own progress and take action. • Provide students with automated feedback based on analytics. • Establish action pathways for all levels of analytics data.

Appendix Table 1: User stories from LAUS workshop

Student-facing learning analytics user stories: As a student
• I want to know that the experience I have had, and previous students, will be used to improve future studies (acting on analytics/co-created). • I need the analytics to cover everything I do whilst learning, so the measurement of my learning is holistic (co-created). • I would like to understand where I am in my study to motivate me to succeed. • I would like to understand my engagement in relation to my cohort so that I can find suitable learning partners. • I would like to understand my study behaviours in the context of previous successful students. • I would like to be able to access tutor level support 24/7 so that I can study sat times that best suit me. • I would like to be able to access relevant materials and support through voice assistants so that I am able to engage in my learning in a wider range of situations. • I would like to be made aware of further relevant study/support services that are available so that I can plan my studies/progression ahead. • I want the opportunity to tell you whether I am getting what I signed up for. • I would like to know who lives in my area studying the same course so that I can buddy up (and be given the option to not make my details known to others). • I would like to know how many others and who is struggling with the same things I am, and how they overcame it, so that I can feel better about myself, learn from their experience and ask for help (and be given the option to not make my details known to others). • I would like the purpose I came to study with you to shape your offer/trajectory. • I would like to make a better choice about my study pathway to choose the right one for my purpose. • I would like to know the learning possibilities available to me. • I want to know which study approaches would help me successfully study my materials. • I would like my AL to tell me when I am falling behind, so that I can alter my study habits/regulate. • I would like to have automated support a) to get quicker feedback about my progress and behaviour and b) so that I can progress at my own pace
Teaching and faculty-facing learning analytics user stories: as a teacher
• I want to know which modules are graveyard modules [that is, modules not drawing in new students but transferring them from other options] so I can cut them (curriculum review) (acting on analytics). • I want to know where the grave yard points are so I can address them. • I would like to know factors influencing learning so that I can take this into account when designing new curriculum. • I need the OU processes (+ funding) to allow me to make changes that analytics says I should (acting on analytics). • I would like to know what students feel about the effectiveness each element of my learning design so that I can improve it. • I would like to identify areas of the curriculum that past students have not engaged with so that it can inform an alternative route through the study materials. • I would like to know if my students are engaged with learning in real-time so I can intervene if necessary. • I would like to understand strengths and weaknesses so that I can support students effectively.

• I would like to know how useful my students found the last tutorial so that I can improve the next one. • I would like to identify when and how a student is failing so I can offer appropriate support. • I want to know what feedback I should give to the students in their module to ensure success. • I would like to offer personalised pathways to support a diverse student body and an inclusive institutional ethos. • I want students to have access to reflective prompts, to show them their current performance and encourage them to reflect.
Professional service-facing learning analytics user stories: as a professional,
• I would like to understand strengths and weaknesses to determine what resources our students require. • I would like to identify students for whom I need to offer proactive support. • I would like to identify students who require additional support, i.e. Disability.
Management-facing learning analytics user stories: as senior manager
• I need to be confident about analytics so I can believe what it's telling me (smart OU). • I need to be confident my staff understand analytics so I can trust them to act in an informed manner (smart OU). • I would like to know whether students feel they are getting value for money so that I can identify priority areas for improvement. • 'We' would like to track students throughout their study, so that we can learn from each student.

[i] The OU initiated a £2 Million Student Experience Project in 2014 to explore the affordances and limitations of learning analytics (Rienties, Boroowa, et al., 2016)

[ii] Since 2011 six of the top 20 most cited articles in Google Scholar on learning analytics originated from the OU, and the OU ranks number 1 in the world in terms of the total amount of articles published in WebofScience (n = 42 out of 1.136 records).

[iii] The Consensus Workshop methodology forms part of a collection of techniques - Group Facilitation Methods (GFM) – that can be accessed through the Institute of Cultural Affairs UK (ICA:UK), a non-profit company specialising in training facilitators both in the UK and overseas. (https://www.ica-uk.org.uk/).