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Title The scalable implementation of predictive learning analytics at a distance learning university: Insights from a longitudinal case study

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Abstract

A vast number of studies, yet mostly small-scale reported exciting innovations and practices in the field of learning analytics. Whilst these studies provide substantial insights, there are still relatively few studies that have explored how the stakeholders' (i.e., teachers, students, researchers, management) perspectives and involvement influence large-scale and institutional-wide adaptation of learning analytics. This study reports on one such large-scale and long-term implementation of Predictive Learning Analytics (PLA) spanning a period of four years at a distance learning university. OU Analyse (OUA) is the PLA system used in this study, providing predictive insights to teachers about students and their chance of passing a course. Over the last four years, OUA has been accessed by 1,182 unique teachers and reached 23,640 students in 231 undergraduate online courses. The aim of this study is twofold: (a) to reflect on the macro-level of adoption by detailing usage, challenges and factors facilitating adoption at the organisational level, and (b) to detail the micro-level of adoption, that is the teachers' perspectives about OUA. Amongst the factors critical to the scalable PLA implementation were: the faculty's engagement with OUA, teachers as "champions", evidence generation and dissemination, digital literacy, and conceptions about teaching online.

Keywords Predictive Learning Analytics; Higher Education; distance learning; scalable implementation; OU Analyse.

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Highlights:

- This study describes a large-scale, longitudinal PLA implementation.
- It presents lessons learnt from the 4-year enactment and evaluation of OUA.
- Faculty, champions, and evidence as facilitating scalability.
- Conceptions of teaching and digital literacy affecting teacher's adoption.

The scalable implementation of predictive learning analytics at a distance learning university: Insights from a longitudinal case study

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Abstract: A vast number of studies, yet mostly small-scale reported exciting innovations and practices in the field of learning analytics. Whilst these studies provide substantial insights, there are still relatively few studies that have explored how the stakeholders' (i.e., teachers, students, researchers, management) perspectives and involvement influence large-scale and institutional-wide adaptation of learning analytics. This study reports on one such large-scale and long-term implementation of Predictive Learning Analytics (PLA) spanning a period of four years at a distance learning university. OU Analyse (OUA) is the PLA system used in this study, providing predictive insights to teachers about students and their chance of passing a course. Over the last four years, OUA has been accessed by 1,159 unique teachers and reached 23,180 students in 231 undergraduate online courses. The aim of this study is twofold: (a) to reflect on the macro-level of adoption by detailing usage, challenges and factors facilitating adoption at the organisational level, and (b) to detail the micro-level of adoption, that is the teachers' perspectives about OUA. Amongst the factors critical to the scalable PLA implementation were: the faculty's engagement with OUA, teachers as "champions", evidence generation and dissemination, digital literacy, and conceptions about teaching online.

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1. Introduction

Across the globe Higher Education Institutions (HEIs) are exploring the opportunities technology affords to provide a consistent and personalised service to students and other stakeholders (e.g., Gasevic, Dawson, Rogers, & Gasevic, 2016; Gelan et al., 2018; Author, A. et al., 2017; Author B. et al., 2016; Tait, 2018). In the last eight years, Learning Analytics (LA) have been strongly 'pushed' forwards by policy makers, managers, teachers, and researchers as a means to address student retention (e.g., Larrabee Sønderlund, Hughes, & Smith, 2019; Zacharis, 2015), improve learning design (Colvin et al., 2015; Ferguson et al., 2016; Macfadyen & Dawson, 2010), and provide real-time actionable feedback to teachers and students (Cheng, Liang, & Tsai, 2015; Jovanović, Gašević, Dawson, Pardo, & Mirriahi, 2017; Scheffel et al., 2017; Tempelaar, Niculescu, Rienties, Giesbers, & Gijselaers, 2012).

A range of mostly western HEIs have started to explore the use of LA dashboards that can display learner and learning behaviour to teachers and instructional designers and provide just-in-time support to students (Bodily et al., 2018; Author A, et al., 2017; Jivet, Scheffel, Specht, & Drachsler, 2018; Scheffel et al., 2017). Furthermore, a range of HEIs have developed Predictive Learning Analytics (PLA) approaches, or adopted existing integrated predictive solutions embedded into their Virtual Learning Environments (VLEs), to help identify students who may be ‘at risk’ of failing (Calvert, 2014; Wagner & Longanecker, 2016).

Although substantial progress has been made in terms of early adoption and uptake of LA in the form of experiments and single-course designs, several researchers have argued that most LA adaptations are mainly on a small, micro level (e.g., Dawson et al., 2018; Gasevic et al., 2016; Higher Education Commission, 2016; Ferguson et al., 2016; Viberg et al., 2018). While some of the LA and technology conferences might give the impression that 'everyone' is using LA, in reality most institutions across the globe, and teachers in particular, have limited or no experience with LA (Ferguson et al., 2016; Ferguson & Clow, 2017; Viberg et al. 2018). There is only a handful of institutions that has adopted LA as a main organisational approach. One such example is the Open University UK (OU) (e.g., Ferguson & Clow, 2017; Higher Education Commission, 2016; Hoel, Griffiths, & Chen, 2017; Raths, 2016). The OU is the first university to implement an institutional ethics policy in learning analytics (Slade & Boroowa, 2014), has a university-wide implementation of PLA for its 170,000+ students (Calvert, 2014; Author A. et al., 2017; Wolff, Zdrahal, Nikolov, & Pantucek, 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 (Author A, et al., 2019; Author B, 2016; 2017).

Nonetheless, a recent study about the state of LA at the OU (Author B, 2019) indicated that there is substantial room for improvement in how the organisation and its stakeholders use LA, in particular: a) Improved communication supported by LA, b) Personalisation to recognise unique distance learners’ needs, c) Integrated design from inquiry to lifelong learning, d) Development of a strong evidence base about what works and what does not. In this study, we focus specifically on the second area; LA could be used to support 'at risk' students struggling with content and assessment, focussing teaching and support staff resources. OU Analyse (OUA) is one approach used at the OU to tackle this issue. During the last four years, OUA has been implemented in 231 undergraduate courses, engaging 1,159 unique teachers and reaching 23,180. A range of studies have shown that OUA is effective both in terms of identifying students at risk at an early stage (Wolff, Zdrahal, Herrmannova, Kuzilek, & Hlosta, 2014), and helping teachers to effectively support their students (Author A. et al., 2017; 2019). Yet, in line with other research (e.g., Arbaugh, 2015; Van Leeuwen 2018), large differences in actual OUA usage by teachers were reported (Author A. et al., 2017; 2019), with some teachers logging in OUA only sporadically. Furthermore, there was substantial divergence in terms of uptake within particular faculties and qualifications. To better understand the complex dynamics of OUA uptake on a large scale and inform strategies of scalable PLA adoption, this study will address the following two Research Objectives (ROs):

RO1: To reflect on the macro-level of use by detailing the degree of OUA usage, challenges, and aspects facilitating adoption, over a period of four years.

RO2: To reflect on the micro-level of use, that of the teaching practice, by detailing the perspectives of teachers who made use of OUA.

2. Literature review

2.1 Predictive Learning Analytics (PLA) in Higher Education

As defined by the Higher Education Commission (2016, p. 53), Predictive Learning Analytics (PLA) *"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"*. Indeed, most learning analytics studies to date have been focused on improving learning outcomes, yet less than 6% of 252 studies reported used LA at a large scale (Viberg et al., 2018). Similar findings were reported by Ferguson and Clow (2017), who after reviewing 123 LA studies argued that most studies were small scale and lacked a strong evidence-based research approach.

During the last four years, the OU has been developing, conceptualising and implementing large-scale PLA applications (e.g., Calvert, 2014; Kuzilek, Hlosta, Herrmannova, Zdrahal, & Wolff, 2015; Wolff et al., 2013), that had a large impact on both the conceptualisation and implementation of LA at other institutions. In particular, one generic PLA system built upon regression analysis of 30+ student indicators (Calvert, 2014) provides 'risk-profiling' to teachers and support services at four time points during a course presentation. In addition to that OUA - a more fine-grained, machine learning PLA system - provided weekly predictions about assignment submission and recommender options to teachers in 231 undergraduate courses (Author A. et al., 2017; Kuzilek et al., 2015; Wolff et al., 2013). Insights from these two PLA systems are provided directly to teachers and student support teams. 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), thus providing direct feedback via a computer or smartphone might not suit certain groups of OU learners. Given the importance of teachers in using LA (Author A. et al., 2017; Author B et al., 2016; Van Leeuwen, 2018), the next section explores some of the key factors that might influence whether or not teachers are likely to use LA in their practice.

2.2 Innovation in Higher Education

2.2.1 The role of the organisation

Higher Education (HE) is a sector often characterised by resistance to change and adaptation (Chandler, 2013; Author B., 2014). In HE, resistance to change is often linked to organisational culture, characterised as one with strong traditions, and clear expectations sustained by both academic and professional staff with long-standing positions (Chandler, 2013). Change may happen at the organisational level (e.g., adoption of technology), yet not endorsed at the individual level (e.g., limited change in actual teaching-practice using technology). Reasons explaining resistance in HE are either organisational or individual such as, faculty members who tend to be reluctant to change, resource allocation, unprepared leaders with a lack of vision, poor communication between involved stakeholders, and personal resistance (habit, fear of the unknown etc.). At the individual level, resistance may be passive or active, the former referring to non-participation and avoidance and the latter to arguing and blaming (Piderit, 2000). The introduction of PLA goes deep into the core roles of teachers and academics more likely causing passive or active resistance to this change (Author A. et al., 2017).

Organisational studies (Chandler, 2013; Piderit, 2000) have consistently found that uptake of new innovations needs to be supported from both a senior management level as well as from the 'shop floor'. For example, working with a large group of course teams on a micro level and for a sustained period of time allowed teachers to become comfortable with using learning analytics (Author B., 2016). At the same time, even after working intensively on a micro level, several groups of teachers remained relatively sceptical towards integrating learning analytics in their practice. Follow-up interviews highlighted that most academics were not necessarily negative towards the change of method, instead they were primarily worried about how data could be utilised by senior management.

In terms of PLA uptake, Dawson et al. (2018) interviewed 32 senior leaders (i.e., Vice-Chancellors, DVS) and found that institutions either followed a top-down instrumental approach to adoption, or an emergent innovators bottom-up approach through a strong consultation process. Yet, most institutions had limited adoption of LA and used them on a small scale. For example, Author A. et al. (2019) interviewed 20 education stakeholders involved in PLA implementation and identified positive perceptions of using PLA especially in distance learning institutions across all participants, yet they noted challenges related to management priorities, teachers, and evidence of effectiveness. PLA adoption in HE could be facilitated by providing institution-specific evidence of effectiveness, proposing specific student support interventions, promoting communication across stakeholder, using PLA data to inform decisions, including teachers in the process of adoption, allocating managerial time for adoption and using PLA to complement the teaching practice (Authors A. et al., 2019; Van Leeuwen, 2018).

In this study, we will reflect on our own experience, as an interdisciplinary group of academics, managers, and practitioners managing the testing and implementation of OUA, and detail the challenges we faced alongside the conditions that are facilitating scalable adoption (RO1).

2.2.2 The role of teachers

Mixed findings are reported in studies assessing the use of PLA data and visualisations with teachers (Author A. et al., 2017; Van Leeuwen, Janssen, Erkens, Brekelmans, 2014). For example, in a study with 28 teachers Van Leeuwen et al. (2014) identified that teachers who received LA visualisations of collaboration activities were better able to identify participation problems. Also, they were found to intervene more often in 'problematic' groups as opposed to a control group that did not receive LA visualisations. Yet, in a follow-up study with 40 teachers, Van Leeuwen et al. (2015) showed that teachers with access to LA were not better at detecting problematic groups but they could provide more support to students experiencing problems. Learning analytics insights were found to influence the teachers' behaviour, by opening up interaction and communication between the teachers and students, leading to pedagogical interventions (van Leeuwen, 2018). Van Leeuwen (2018) found that although teachers found PLA visualisations useful, some of them found it difficult to connect the PLA information to concrete interventions. Positive outcomes are also reported by McKenney and Mor (2015) reporting that the teachers' professional development was enhanced by engaging with analytics software.

Through a mixed-method study at a distance learning institution, Author A. et al. (2017) found mixed effects on student performance when teachers were given access to PLA, yet usage analysis showed that teachers made only limited use of PLA in their practice that could explain these mixed effects. Follow-up interviews with teachers revealed that teachers had positive views about using PLA in teaching as they recognised their usefulness for complementing the teaching practice and being 'on top of things'. Also, in a multi-methods study with 59 teachers, and more than 1,300 students, Author A. (accepted 1) identified that teachers engagement with predictive data is the second most significant factor explaining student performance, after previous best score. In a follow-up study with 189 teachers and 14K students in 15 undergraduate courses, Author A. (accepted 2), identified that teachers who made 'average' use of OUA benefited their students the most, as they had significantly better performance than their peers in the previous year's presentation during which, the same teachers made no use of PLA. Yet, Dazo, Stepanek, Chauhan, and Dorn (2017) analysed usage data of 14 teachers and identified that frequency of visits decreased between semesters. A follow-up focus group with six teachers pointed out that teachers faced challenges in interpreting the data and this led some of them to shift to other methods of monitoring students' progress, such as reading their posts.

Overall, there is an emerging body of evidence showing that PLA can be effective in some cases, yet not in others, raising the need for more, robust, longitudinal research beyond a single context or discipline. In order to provide convincing evidence to key stakeholders, including teachers, as argued by both Ferguson and Clow (2017) and Viberg et al. (2018) it is essential that the learning analytics community shows consistent and reproducible results about the conditions under which PLA may or may not work. Elaborating on our previous work, in this study we detail the perspectives of eight online teachers who were given access to OUA, in an effort to identify factors influencing OUA adoption, thus informing future practice.

3. Theoretical underpinnings

3.1 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) (Davis et al., 1989), founded on the well-established theory of Planned Behaviour (Ajzen, 1991), states that the intention to use a technology is influenced by two factors: (a) *perceived usefulness* (PU: for example, whether a teacher thinks that the use of PLA can enhance their teaching or help students' performance) and (b) *perceived ease of use* (PEU: for example how easy or difficult is (perceived effort) to use PLA.

A range of studies have found that users' technology-acceptance, as conceptualised in TAM has considerable impact on the adoption of information systems. The influence of PU and PEU has consistently been shown in educational research (Ali, Asadi, Gašević, Jovanović, & Hatala, 2013; Pynoo et al., 2011; Teo, 2010). TAM has proved to be highly informative in explaining teachers' uptake of educational technology (Šumak, Heričko, & Pušnik, 2011). For example, Teo (2010) found that PU and PEU were key determinants of the attitudes towards computer use of 239 pre-service teachers. Also, in an experimental lab study with 95 teachers Author B. (2018) identified that the great majority of teaching staff perceived LA visualisations as being useful (PU), yet only one third of them as being easy to use (PEU). This was explained by the number of tools examined concurrently and their early level of development. These insights indicate the teachers' recognition of the significance of using analytics to support students yet they also raised the need for additional support and teacher training that can facilitate usage. Similarly, Author A. et al. (2017) analysed interview data from six online teachers and identified contradictions between actual PLA usage (technology acceptance) and PU, suggesting that greater perceived usefulness may not necessarily result in greater usage and acceptance.

3.2 Community of Inquiry (CoI)

Teachers adopt or develop different approaches to teaching that have been linked to different 'conceptions' of teaching (Richardson, 2005). Kember (1997) proposed five distinct conceptions of teaching ranging from teacher to student-oriented ones:

1. Teaching as imparting information
2. Teaching as transmitting structured knowledge
3. Teaching as an interaction between the teacher and the student
4. Teaching as facilitating understanding on the part of the student
5. Teaching as bringing about conceptual change and intellectual development in the student.

These conceptions are found to be highly connected to different disciplines, with teachers teaching on the same discipline sharing similar conceptions, as well as been connected to contextual factors that can affect teachers' original conceptions (e.g., traditional views of teaching by senior staff) (Norton et al., 2005). In online settings, teaching is rather distributed amongst individuals with different expertise and with or without pedagogical backgrounds (Pelz, 2010; Author B. et al., 2016). Therefore, teaching conceptions may vary depending on the role each professional has in the preparation and presentation of an online course, such as designing learning activities or facilitating interactions with students. In this study, we engaged in particular with the so-called Associate Lectures (ALs), that is online teachers the role of whom is to provide support and guidance to a group of 15–20 students. ALs are required to know how to use information communication technology for teaching and supporting students, accessing information in relation to students, facilitating contact with academic units, and dealing with administrative responsibilities.

The provision of personal and pedagogical support or achieving 'online presence' is rather challenging, yet one emphasized in the literature due its important role in scaffolding students' success in online settings (Lin, Wang, & Lin, 2012; Muñoz Carril, González Sanmamed, & Hernández Sellés, 2013; Author B., 2018). Online presence is the need for interactivity and encouraging learners to regulate their learning (Kilgour, Reynaud, Northcote, McLoughlin, & Gosselin, 2018). It can be achieved through frequent and varied communication between teachers and students, such as providing opportunities for individual dialogue with the teacher that encourages the formation of relationships, the development of shared experiences, and the decrease of relational distance (Dockter, 2016). Exemplary online educators are viewed by students as those who challenge learners to perform beyond their current capacity and have high expectations for them, as well as those who affirm personal growth and influence learners through subject matter expertise and strong online presence (e.g., feedback and email communication) (Edwards, Perry, & Janzen, 2011).

In this study, we adopt the Community of Inquiry (CoI) framework (Garrison, 2007) as a means to frame and explain ALs conceptions about teaching and how these may potentially relate to the degree of usage and adoption of OUA. The CoI suggests that meaningful learning experiences are structured in interactions between students and teachers and these require social, cognitive and teaching presence. Social presence is the sense of community and the development of quality interactions between teachers and students. Cognitive presence refers to ideas and their elaboration through dialogue, for the construction of individual meaning-making. Teaching presence refers to teachers facilitating and giving direction to these discussions. The CoI has been used in several studies to analyse successful or exemplary teaching experiences and teachers both in online and offline settings (Arbaugh, 2014; Edwards et al. 2011; Garrison, 2007).

In this study, we detail the perspectives of (a) an interdisciplinary project management team by reflecting on the OUA degree of adoption, challenges, and aspects facilitating adoption during a four year implementation (RO1), and (b) eight teachers with access to OUA by identifying how technological and pedagogical factors potentially explain the degree of OUA adoption at the level of the teaching practice. To analyse teachers' perspectives we utilise two complementary frameworks: TAM informing our understanding of adoption by teachers as being related to the characteristics of technology or PLA and CoI as being related to teachers' pedagogical conceptions about online teaching and learning (RO2).

4. Methodology

4.1. OU Analyse

OU Analyse (OUA) is a predictive system used to identify learners at risk of failing their studies (Fig. 1). OUA predicts on a weekly basis whether a given student will submit or not their next teacher-marked assignment. The OUA dashboard visualises predictive information about who is at risk of not submitting their next assignment for individual students, as well as VLE engagement, and assignment submission rates at the cohort level. It uses a traffic light system to pinpoint: in red students at risk of not submitting, in amber those with a moderate probability of failing, and in green those who are likely to be successful.

[insert Figure 1 here]

Predictions of students at-risk of not submitting their next assignment are constructed by machine learning algorithms that make use of two types of data: (a) static data: demographics, such as age, gender, geographic region, previous education, and (b) behavioural data: students' interactions within the VLE hosting a course. These sources of data were shown to be significant indicators of predicting students' assignment submission

(Kuzilek et al. 2015; Wolff, Zdrahal, Nikolov, & Pantucek, 2013). To assess the quality of predictions by OUA, in each week confusion matrix values (True Positive, True Negative, False Positive, False Negative) for all courses are summed up in order for small size courses to influence less student performance.

OUA employs three machine learning methods: (1) Naïve Bayes classifier (NB), (2) Classification and regression tree (CART), (3) k-Nearest Neighbours (k-NN). Those are used to develop four predictive models: (1) NB, (2) CART, (3) k-NN with demographic data, and (4) k-NN with VLE data. Combining results from these four models was shown to improve overall predictive performance. Two versions of k-NN was used due to the different nature of the values measured, i.e. numeric VLE data and categorical demographic data. These four models consider different properties of student data and complement each other. Each model classifies each student into classes: (a) will/will-not submit next assessment and (b) will fail/pass the course. The final verdict of the prediction is done by combining the outcomes and using voting techniques from all four models (Kuzilek et al. 2015; Wolff et al, 2013). In brief, the result of the prediction is 'will-not submit next assignment' if three or all four models give a prediction of 'will-not submit'. The result of the prediction is 'will submit' if zero, one, or two models vote 'will- not submit'.

4.2. Analysis of stakeholders' perspectives

4.2.1 Project management's perspective

The first part of this study reflects on OUA degree of usage, challenges and factors facilitating adoption during a period of four years (RO1), as perceived by an interdisciplinary project management team (the authors of this paper). The first step of this analysis was to visualise OUA adoption in terms of numbers of teachers and other staff accessing OUA per academic year. The second step was the production of usage statistics across course presentations showing the level of teachers' usage across the four university faculties. The third step was to discuss these graphs by reflecting on challenges and aspects facilitating adoption.

4.2.2 Teachers' perspective

The second part of this study details the perspectives of eight teachers who were given access to OUA, as captured through two, 4-hour evaluation workshops. The aim of the workshops were to identify factors that potentially explain the degree of OUA adoption by teachers, and that could inform further steps in terms of how to facilitate adoption and enable a scalable implementation. In the next sections we detail the process of data collection and analysis.

4.2.2.1. Sample

The eight teachers who joined the two face-to-face workshops (N=8) were self-selected and identified after responding to an email from the project management team requesting for volunteers to take part in OUA evaluation workshops. Financial incentives in the form of travel reimbursement and subsistence were offered to participants. The response rate was relatively low, but consistent with previous OUA evaluation studies (Author A et al., 2017). The authors recognise the self-selecting biases related to this approach of identifying participants (Author B, 2016; Torgerson & Torgerson, 2008) and consider this in the data analysis and interpretation. Participating teachers were 4 male and 4 female, from the Science (n=7) and Business and Law (n=1) faculties, with an average teaching experience at the OU 14 years, and a relatively high mean age of 54 years.

4.2.2.2. Process of data collection and analysis

Data were collected from two, 4-hour, face-to-face workshops with teachers who had access to OUA. The workshops resembled the format of focus group interviews (Vaughn, Shay Schumm, Sinagub, 1996); they built on our previous work of interviewing teachers about their experiences of using OUA (Author A. et al., 2019), and in line with Van Leeuwen and colleagues (2015;2018) aimed to gain additional insights by allowing participants to exchange ideas and discuss possible disagreements in relation to their perceptions about OUA, such as whether they perceived OUA as useful, under which conditions, and why. All participants consented for the sessions to be audio-recorded and anonymised data to be used in future reporting and dissemination activities. Drawing from TAM and CoI, the workshop aimed to collect data about: (a) participants' perceptions and practices about online teaching (see CoI) and (b) their understanding, perceptions and future intentions in relation to OUA (see TAM). They were structured around a set of group and individual activities participants were asked to complete:

- *Activity 1: "Before OUA" (group discussion, audio-recorded):* How would you characterise your relationship with your students? When and how often do you get in touch with them? Do you monitor their activities online and if so how? What is your approach to students who may struggle with their studies? *(see CoI)*
- *Activity 2: "OUA usage patterns" (individual activity, paper-based):* Participants were asked to complete a worksheet about OUA usage, which included a set of screenshots and questions about OUA access, features they use, and their understanding of it *(see TAM)*
- *Activity 3: "Perceptions about OUA" (group discussion, audio-recorded):* Do you find OUA or specific features of it particularly useful and if so, in what respect? How do you use or would you use OUA with your students? What conclusions can you draw about student performance? Did OUA change your existing teaching approach in any ways? *(see TAM)*

Workshop data from Activity 1, 2 and 3 were entered into NVivo. We used thematic analysis (Boyatzis, 1998; Kvale, 1996) to identify emerging themes related to the aims of the workshop such as the existing student support approaches, usefulness and challenges (see Table 1). Author 1 and Author 5 coded the data independently and compared emergent themes to ensure inter-rater reliability. The inter-rater percentage agreement, which equalled to 85%, was calculated by dividing the number of times both researchers agreed by the total number of times coding was possible (Boyatzis, 1998). As a result of this comparative exercise, few codes were renamed to enhance comprehension and other were merged together to avoid overlaps. After agreement was reached, changes were fed into the coding of the rest of the transcripts.

[Insert Table 1 here]

5. Results

5.1 Project management's perspective

The first step of this reflective account was to visualise the degree of OUA adoption over the last four academic years (2015/16 - 2018/19), in terms of (a) numbers of unique teachers, and (b) usage patterns of unique teachers over the course of a presentation. The number of teachers accessing OUA at least once was shown to increase considerably over years (see Fig.2), with 52 teachers in 2015/16 and 1,159 in 2018/19. Yet, the overall percentage of those accessing OUA out of those who were granted access per year varied between 89% and 33%.

[insert Fig.2 here]

Figures 3-6 illustrate the average weekly usage of OUA by online teachers across the four university faculties. In 2015/2016 (Fig.3), teachers in Education courses were more actively engaged with OUA, in particular the first half of the presentation. The overall average engagement dropped over time across all faculties. In 2016/2017 (Fig.4), teachers in Social Science were more actively engaged than their peers in any other faculty. In 2017/2018 (Fig.5), there is considerable drop in participation especially in Social Science, with Science being the most active faculty. In 2018/19 (Fig.6), there is participation across all faculties, with Business/Law being most active, especially during the first 10 weeks of the course presentations.

[Insert Fig.3-6 here]

The OUA project built on existing analytics work at the OU and aimed to generate evidence about its impact on improving student retention and performance, a strategic objective of the university. It was set-up as an interdisciplinary project with colleagues from faculties, ALs, academics, education managers, IT and evaluation experts. Several channels of communication were set up that facilitated interactions including support mailbox and forum, training sessions, and regular meetings with involved stakeholders.

In 2015/16, OUA was piloted with a small group of volunteer teachers and course chairs on 10 courses across three faculties (Science, Social Science, Education). Teachers were self-selected resulting in a 89% OUA usage out of those teachers who were given access to the system (see Fig.2). Project evaluation focused on issues of OUA access and their relationship to student outcomes (Author A. et al., 2017). In 2016/17, a new round of piloting was set up with 24 courses. The evaluation plan foresaw the use of experimental methodologies (RCTs, A/B tests), due to their robustness in generating conclusive evidence of impact on student outcomes.

Yet, this methodological approach was not taken forward by the faculties; during that period, the university went through a tremendous institutional change related to the teaching policy, that caused concerns about the teacher workload and resulted in faculties being unwilling to engage with the pilots. Therefore, the methodological approach was revised and participation on a voluntary basis was adopted. This resulted in a significant drop of participation (33%). Additional factors were also related to that drop, as flagged in the communication with faculties and teachers, including the simultaneous running of other retention initiatives, the introduction of a new tuition technology (replacement of Blackboard with Adobe Connect), teachers' requesting extra payment for participation in piloting, and the renegotiation of teachers' employment contracts. These issues were mainly coming from the Education and Business/Law faculties potentially explaining the low OUA usage (see Fig.4). They also affected piloting in 2017/18; only two faculties (Education and Science) participated officially in pilots with teacher volunteers from 22 courses, with 63 less teachers accessing OUA compared to last year (see Fig.5).

In 2018/19, a major change took place; all faculties agreed to embed a link to OUA in the teachers' support homepage, thus enabling easy access to all teaching staff across the university. Prior to that, staff were expected to access OUA through an independent URL. This decision resulted in a considerably larger number of teachers accessing OUA - 1,159 unique teachers, as compared to a few hundred or less in previous years, and had certain implications. It meant that not only teachers, but also course chairs and managers recognised the value of the tool and agreed on supporting its use across their faculties (see Author A. et al., 2019). Figure 7 showcases that an average of 35% of teachers and 57 % of course chairs accessed OUA. We will comment further on Business/Law as the faculty that systematically encouraged usage of OUA - by developing a coherent teaching and intervention strategy and actively promoted the availability of OUA as a tool to monitor students' progress as well as a means to trigger possible interventions - resulting in more than half of the staff (56.5%) accessing OUA, the highest percentage across faculties. This suggests that faculty engagement can considerably facilitate the degree of adoption towards a scalable implementation.

Two other factors built in the design of the project may well facilitate adoption: (a) Four teachers acting as "the OUA champions" were recruited to provide training and support to teachers, share authentic, practice-based examples about how to use and act upon OUA insights, and act as an interface between the technical team and the user base. These teachers raised awareness and generated interest in OUA across the university. Yet, this specific teacher-centred communication channel also revealed a lack of digital skills amongst some of the teaching staff and highlighted the need additional support in relation to interpreting OUA visualisation and effectively supporting students at risk. (b) The pilots were systematically evaluated resulting in a growing evidence-based account about the effectiveness of OUA. Insights were regularly disseminated by different members of the project team in faculty and university wide events raising awareness and sparking further discussions and interest about OUA. Education managers proposed this as a factor that can facilitate adoption (Author A. et al., 2019).

[insert fig 7 here]

5.2 Teachers' perspectives

Figure 8 shows the average usage pattern of OUA by the eight workshop participants, up to the day before the workshops took place. Four of the teachers had a relatively active engagement with OUA (P2,3,4,5) whereas the rest of them a relatively low participation. Yet, P1, P6 and P8 are shown to access OUA approx. around the weeks when assignments are submitted. Due to the nature of the workshop (audio recording of focus-group discussions), we could not map OUA usage with teachers' perspectives analysed below.

[insert fig.8 here]

5.2.1 Existing student support approaches

The discussion of eight teachers around how they approached and supported their students revealed a great depth of variation and a degree of personalisation in the proposed student support mechanisms. This variation indicated that there was no standard or evidence-based way of how and when teachers approached students in order to ensure that they progressed with their studies. This was a decision made by each individual teacher based on their own perceptions about how to best support students' learning. Participating teachers agreed on the need to contact students, yet the frequency and way of contacting students varied considerably, as shown in Fig.8.

In terms of how often these eight teachers got in touch with students, some teachers explained that they were very proactive and they tended to email, text, or phone their students, as well as regularly posting discussion threads in forums. Others got in touch with certain students, such as those with accessibility needs, assuming that these groups of students might need additional support. Others mentioned that certain courses might have requirements they had to follow such as setting up an appointment with students during the first two weeks of a course. As explained:

- *Female 3: "I tend to ask what they want from it, if I see someone that has got a D marker, can you let me know how you want me to help with your study [...] Like I say I'm not be like [name of teacher removed]. I don't phone all my students, I don't chase them up because as I say they are adult learners."*
- *Male 4: "Well I don't chase them every week, I send out lots of emails and stuff on the tutor group forum...I only give them another phone call if they are falling behind or not logging on."*
- *Female 3: "Are all students positive about that?The reason I don't do that is because students will say I work at the [Name] University and the reason I study with that University is because it is distance learning and I don't expect you to be checking up on me every week."* (Workshop 1)

The above excerpt reveals that the frequency of contacting students is associated with the teachers' conceptions of who the students are and their assumptions of why they study online. In particular, 'sending out a lot of emails' might be perceived as 'chasing' or 'spoon feeding' students, and therefore viewed as inappropriate to adult learners and one that may inhibit students from becoming independent learners. Also, studying at a distance learning institution entailed certain connotations such as that students do not need to be checked regularly. The excerpt showcases two opposing student support approaches: Male 4 was acting over and above the course requirements, contacted students regularly and through varied means, while Female 3 was less proactive perceiving students as not needing frequent communication.

In addition to the personalised ways of contacting students, teachers explained that students themselves and/or the university Faculty might explicitly define or influence how students are contacted. Some students are interested in being known by their names, and have personal contact with the teacher, whereas others view teachers as those marking assignments. Students' perceptions of the role of the teacher can be affected by faculty and course regulations:

"Some students the ones that really want you …my name is Winston and I want everything I do in the university to say my name, whereas other students will say, I'm studying multiple things and you are just the person marking the stuff ...As far as they are concerned ... you just happen to be the person that is going to mark their work ...the starters they tend to know you as the face…Also, how your faculty works it, we have this thing where, I have my students but they can go to any tutorial and so I'm not their face really" (Female 3, Workshop 1).

A variety of approaches is used as a means to communicate and support students, including emails, phone calls, forum threads. Teachers tend to prefer emailing than phoning students because most students may not answer their phones or be unavailable *"putting the kids to bed or just making dinner"* (Female 5, Workshop 1). Yet, emailing students does not ensure that students will reply *"But at least, I like emails because you have got a written record"* (Female 3, Workshop 1). In addition to that, some teachers devised and tested additional approaches to supporting students such as the "cuppa sessions" (cup of tea sessions): *"One of the things I started doing this year ... I said I will always be in the tutorial group Tuesday 8-9; they never turn up, never"* (Male 3, Workshop 2 **).** The fact that students may not be responsive or ignore the communication of teachers is a major challenge reported by participating teachers. Yet, how this challenge is addressed depends on how teachers perceive and explain the behaviour of those "ghost" students. In the excerpt below, the teacher views "non-responsiveness" as unintentional:

- *Female 2: "I say this is the module you signed up for, these are the requirements, it's a very short letter ...and I would like you to please respond to this email because I need to know this communication is working [...] if they don't respond my assumption is they didn't get it. I always treat them, as they haven't got it, the email address is wrong."*
- *Male 1:"So if they don't respond you bombard them with more emails until they have had enough and they respond?"*
- *Female 2: "Yes. Basically, they get the second email if they don't respond ...I assume the email address is wrong, it has nothing to do with the email and so then I will send you a letter, [...]I never accuse them of not responding intentionally I always assume there are external circumstances prevented them from replying."* (Workshop 2)

In terms of recording and keeping track of communication with students, teachers either "*put the students name in and search the whole email history that is behind the conversation"* (Female 2, Workshop 2) or develop their own working sheets where they note down the student contact history. As shown in the discussion below, not all teachers are as systematic in their monitoring approaches. This discussion reveals the need for tools that can help online teachers in the process of monitoring communication with students as well as the need to test and mainstream an effective approach of monitoring student progress and interactions.

"Anything I have done with a student I have [it] on my A4 sheet of paper...non-submission of an assignment I send an email and if it's a double R, I sent two reminders if you haven't submitted...If I put an E...it means I gave you an extension...X means got the TMA everything is fine...I can immediately see I need to email X,Y and Z". (Female 2, Workshop 2).

4.2.2 Accessing OUA

Participants noted that they tend to use OUA at the beginning of the course, close to the submission of a TMA, when they have concerns about specific students and, two of them on a weekly basis. As explained: *"It depends how active my students are in the Tutor Group Forum/email. If they are active then not often, if not then I can use it as a monitoring tool and so more often."* (P2, Workshop 1). At a follow up question about "At what specific points during the duration of a module presentation [do you use OUA] ?" the majority said 2-3 weeks before the submission of a TMA, others said early in the life cycle of a course, one participant said monthly and another one every Wednesday when the system updates predictions. These responses showcase that the actual usage of the system is mainly linked to the assignment submission deadlines and when students are silent or teachers have concerns about.

4.2.3 OUA Features

Teachers commented on the usefulness of VLE data in identifying whether students are engaged with the course material, in particular, the number of clicks and the tasks that have been checked by them throughout the week. This is viewed as an aspect of student participation that cannot be monitored in another way, and one that is provided systematically and on time in order for teachers to react and support students who are shown to face challenges:

'OUA gives me another depth, tells me all the online activity which is important ... that is something I cannot monitor from home, I have my papers I only have my feedback every eight, or four to eight weeks and that is sometimes too late, if someone is on a level two Physics course because they don't understand the maths that is used by the time the TMA comes there is a high chance I have lost that student, so seeing lack of activity in the beginning that the student is not getting past chapter one/chapter two would be really useful information.'(Female 2, Workshop 2).

They also commented on the line graph comparing an individual student's level of engagement to the whole cohort of students, and its usefulness in identifying whether a student is performing better or worse than the average student. As explained: *'I believe it is seeing the visual of student's engagement and also to get a sense of the general cohort engagement so you can compare.'*(Male 1, Workshop 2).

In the individual Activity 2, the majority of participants (n=6) circled multiple features of OUA including both the VLE and predictive data as being useful, including features such as predictions at student level, risk of failure, risk of non-submission, next assignment prediction, VLE graph. Other features such as the time machine, the nearest students' comparison, trends and filtering were less often selected. One teacher circled only the VLE data and one other only the predictive data. It was not clear which source of information was perceived as the most significant as some participants assigned a star to VLE data, others to predictive data and others to both sources of information. As explained: "Predictions - tells me at a glance what a student is achieving/not achieving and student module data tells me individual student engagement data" (Participant 8) and "Seeing how much they are interacting with the website is most useful as it gives an idea of whether they are keeping up with the work via the VLE." (Participants 2).

4.2.4 OUA usefulness

The OUA usefulness was discussed in relation to:1) specific features of the OUA dashboard and how these can help make informed decisions, 2) the design of online courses, in particular whether they are entirely hosted online or they also have offline components, such as printed material, 3) type of students e.g., new to the university. Teachers perceived OUA as a tool that can help in identifying students who struggle with their studies and they need extra support, or they need a reminder that they should engage with the online material. Students who flagged as "green" are viewed as not needing support: *"It's quite good to find those ones that fall between the cracks, the ones that are struggling and asking for help [...]then there's ones on green and you think I can pretty much ignore them, they are doing the work.''* (Female 1, Workshop 1**).**

Some teachers viewed OUA as the only means for gaining information about their students' engagement with the online material. As explained below, without OUA the respective teacher could not know whether their students face difficulties and intervene. Other teachers viewed OUA as a tool that can save them time by not having to access and check dispersed sources of student information, assuming that they can find similar student information elsewhere. In particular, they make reference to student data in the university's portal, such as the last time a student logged into VLE, that can inform about whether a student is engaging with the material:

"I'm concerned about students and see evidence that things are not right, I can contact the student a week or two weeks before the TMA and say is everything ok? I didn't have the tool before because...I didn't know when the student was engaging at all or not.''(Female 2, Workshop 2).

"How to help students in a better way... this is a very clever little tool... if you say to an AL how you can save yourself an hour a week going through the data then it's starting to look very promising.''(Male 1, Workshop 2)

Participating teachers viewed OUA as particularly useful for students who are new to the university and who more often face challenges. The university under study has an Open Entry policy which means that any student with no previous qualifications can join the university. This policy has certain implications in terms of how best the university can identify and support newcomers who may face difficulties. Teachers viewed OUA as a tool that can help "tailor themselves" to individual students, especially year 1 undergraduate students, who are less likely to get in touch and request for help, as opposed to more experienced students (e.g., Level 3): *"They don't know what they are doing...and it's up to you to make sure you can help them out so any information on level 1. Level 3 you know, you know if there is a problem they are just as aware of it as you."* (Male 3, Workshop 2)

In addition, participating teachers perceived OUA as particularly useful when a course in entirely hosted on the VLE and has no offline components such as links to printed material (e.g., books). OUA information about courses with offline components may present misleading information about students, by showing them as not interacting with VLE, when they may be reading material offline. In these cases, teachers have no information as to whether students engage with printed material and OUA is less likely to give them reliable information either: *"my module is mainly with books, so they work in the VLE then get told go and read that chapter. You can at least see if they are engaging in the VLE...So at least then you have some idea of what they might have looked at."* (Female 1, Workshop 1)

4.2.5 Understanding of OUA

Data literacy was a theme that emerged when teachers were asked to note down their understanding of OUA features. While overall participants were aware of what the VLE and predictive graphs mean, some noted that they do not understanding features such as the filter functionality (Participant, 8), or their understanding of other features was not correct. For example, Participant 2 explained: *"VLE data shows a comparison of my cohort's interaction with the VLE compared to another cohort...Time machine can see an individual's interaction with the VLE compared with the whole unit cohort."* This interpretation is not correct as VLE data show how the entire cohort of students (not only the teachers' group) compares to last year's cohort whereas time machine enables preview of cohort and student activity in previous weeks of a course.

Aligning with the above observation, teachers raised the need for hands-on, collaborative workshops about OUA and ways of acting upon data. They contrasted the format of the OUA training sessions to the workshop design of the present study; the former are online conferencing sessions delivered by teachers-experts in using OUA and they mainly showcase OUA features and functionality and ways to support students. What is missing from these sessions, according to participants, is opportunities to engage and use OUA, raise questions and discuss with colleagues: "*I think what would be useful is...workshops where you have people sitting in front of a computer and they can work through the data themselves, like hands on learning of the possibilities...it's a group where people can work through the data together and see all the aspects, doing an OU live session is quite nice but you have forgotten half of it afterwards.'' (Female 2,Workshop 2)*

4.2.6 OUA challenges

Participating teachers commented on specific aspects of OUA that could improve their engagement with the system, related to:

(a) Selection of OUA features: Teachers are found to value certain features of OUA more than others, for example, as explained below, cohort-level data is viewed as not useful at all, and therefore teachers should be able to select the OUA features they would like to access: *"Could you actually say to individual Tutors which data do you want? ... Some of the other stuff I look at every four or five weeks if I could pick and choose what data I got when just by default" (Male 3, Workshop 2)*

(b) Accuracy of predictions: Teachers expressed concerns in relation to the accuracy of student predictions, as explained: *"looking at the prediction of OU Analyse, it said a student would fail, it just happened to be a student I met at a face to face tutorial I thought if the student makes the effort in this tutorial is to be very well...I don't know what happened to this student now but I like that I could say no, I think your prediction on this case was wrong'' (Female 2, Workshop 2).* Issues reported as affecting OUA accuracy were TMA extensions, which are not always recorded by the system, and the regularity of updating OUA data, which takes place once a week, rather than daily: *"The whole week layout, it means sometimes by the time you know someone is not logging in almost two weeks have gone by''(Female 3, Workshop 1)*

5. Discussion

This study described the large-scale implementation of OUA at a distance learning university by reflecting on the *macro-level* of use, in particular the OUA degree of adoption, challenges and factors facilitating implementation over a period of four years (RO1) and the *micro-level* of use by analysing the perspective of eight teachers who used OUA (RO2). The graphical analysis of the number of teachers using OUA at least once revealed a significant increase in unique users during the last four years with 52 users in the first year and 1,159 in the last. Yet, the degree of OUA usage by those users was shown to vary across academic years and faculties, with different faculties showing greatest engagement over the years, in particular the first half of a course's presentation.

The four year enactment and evaluation OUA, through a series of pilot studies, was facilitated by a university-wide interest in LA, in particular how LA insights could help the institution tackle a major challenge in online learning, that of student retention. This interest is evident in the university's financial investment on the project and the formation of a relatively large interdisciplinary team of academics including faculty representatives, online teachers, academics, education managers, IT and evaluation experts. This set-up gave a 'voice' to a range of stakeholders involved in PLA and facilitated communication and interactions. This meant that OUA-related problems could be easily communicated, negotiated and potentially solved. While the first year of evaluation was relatively 'smooth' with 80% of participating teachers accessing OUA yet mixed outcomes in terms of OUA effectiveness (Author A. et al., 2017), the two years to come were proven particularly challenging, with this percentage dropping significantly, yet with volunteers interested in trying out OUA. Teacher-related institutional changes (i.e., tuition policy, systems' use, employment contracts, payment for joining pilots, other retention initiatives) resulted in faculties being resistant to rolling OUA across their courses and enabling data collection through experimental methodologies. Yet, evaluation work after been adjusted, was carried out with emerging evidence of effectiveness especially when teachers make sufficient use of OUA (Author A. et al., accepted 1,2).

An impressive increase of numbers was observed the last year of enactment and this is more likely due to faculties recognising the value of PLA (see Author A. et al., 2019) and promoting use across their all of their courses. A prominent example of scalable implementation took place in Business/Law; this faculty developed and promoted a coherent teaching and intervention strategy resulting in 56.5% engagement across all of the staff the highest across the university. Other aspects that contributed to raising awareness about PLA across the university and potentially assisting adoption were the 'teachers-champions' approach - OUA training session and support delivered by teachers to teachers thus sharing the 'same language of communication' and the systematic production of evidence of impact and their dissemination across and beyond the university.

Focus group discussions with experienced middle-age teachers provided insights about the micro-level of use; they revealed a diversity of approaches in relation to contacting and monitoring students and their progress. Some teachers were considerably proactive and systematic while others were acting on a need to know basis. These practices were shown to relate to certain conceptions of teaching, in particular perceptions of online students as being either independent learners or requiring constant monitoring, support, and communication. One of the major challenge teachers reported was the fact that online students tend to not respond to their communication. Aligning with the above conceptions, some teachers were very persistent in contacting students, till communication was established, while others were less active and ceased efforts after a few unsuccessful attempts. It is noted that the great majority of participants are from the same faculty (Science), yet in contrast to existing studies (Norton et al., 2005) they were found to share different conceptions about what teaching looks like in online settings. Some teachers were shown to systematically pursue frequent and systematic communication that contribute to the development of online presence and the formation of relationships with students (Docter, 2016). Yet, others viewed students as not requiring this type of support and communication, contradicting the self-reported need of students for online presence that can lead to success (Lin, Wang, & Lin, 2012; Muñoz Carril, González Sanmamed, & Hernández Sellés, 2013; Author B., 2018).

It could be argued that the lack of an established, university-wide policy as to how teachers should communicate and monitor students resulted in a variation of approaches not always in the benefit of students. Some of these approaches are less likely to promote the development of a Community of Inquiry (CoI) (Garrison, 2007), as the limited interaction between teachers and students is more likely to inhibit, in particular, the development of social presence. In terms of cognitive and teaching presence, the fact that the tuition policy at the university under study requires synchronous teaching sessions at certain points doing the lifecycle of a course, could potentially contribute to meaning-making through teacher's facilitation.

Access to OUA was mainly linked to assignment submission deadlines and students who were "silent" or raising concerns to teachers. What is yet to be explored is whether this frequency of accessing OUA is adequate for intervening on time. In a relevant study, Author A. et al. (accepted 2) showed that a certain degree of usage enabled teachers to achieve better learning outcomes compared to previous years when they did not use OUA. In terms of whether certain features are perceived as more useful, a discrepancy was observed between the focus-group discussions and the individual paper-based activity. In the former, participants commented on VLE data as being very useful for the ongoing monitoring of students' participation, yet in the latter they considered both VLE and predictive data as being equally significant. Drawing from TAM, they expressed high levels of PU, especially under specific conditions: (a) identifying students who struggle with their studies and they need extra support. Students flagged as "green" were viewed as not requiring support. This perception contradicts existing literature noting the need of students for, not only passing a course but also challenge and growth that can be facilitated through a strong online teachers' presence (e.g., Lin, Wang, & Lin, 2012), (b) OUA as a tool that can save them time by not having to check on distributed sources of student information, (c) OUA particularly useful for monitoring newcomers to the university and for whom previous information is relatively limited, and (d) courses entirely hosted on VLE with no links to printed material.

In terms of PEU, teachers did not express any significant concerns in terms of difficulty in accessing OUA, apart from their need to choose OUA features they deem more significant and improving the accuracy of predictions. What it was particularly surprising was the fact that some teachers' understanding of OUA was either limited or inaccurate. Teachers were found to have wrong or lack of understanding of specific features of OUA. This may be an indication of low PEU that could affect the degree of technology acceptance or systematic OUA use. In the same line of thinking, specific teaching perceptions i.e., students do not need constant monitoring may be an expression of low PU of the system explaining limited usage of OUA by some teachers. Yet, the fact that teachers raised the need for interactive training may be an indication of change in PU, after discussions with colleagues in the workshops, and approach that could facilitate adoption in the future.

6. Conclusions

This paper reported on one of the few studies (Viberg et al., 2018; Ferguson and Clow (2017), implementing and evaluating on a large-scale and over a period of four years, a PLA initiative in Higher Education. It detailed the perspectives of stakeholders involved in the macro- and micro-levels of adoption, in particular the project management, reflecting on the organisational level of adoption, and teachers, reflecting on the teaching practice. It showcased that an emergent bottom-up approach through a strong consultation process **(**Dawson et al., 2018) and support by both the senior management and the 'shop floor' - teachers (Chandler, 2013; Piderit, 2000) can facilitate scalable implementations. Such approach could be enacted by distinct interdisciplinary teams that are allocated time (Author A. et al., 2019) to work across and within the different levels of an organisation to curate perspectives, negotiate ideas and tackle challenges. The engagement of teachers as 'champions' and faculty representatives in the process of piloting and evaluation alongside the systematic generation of evidence of impact (Author A. et al., 2019) were shown to influence positively the process of evaluation and degree of adoption, by allowing time for technical developments in response to users' needs and raising awareness of PLA across the university.

Yet, the degree of OUA usage across courses remained relatively limited (Author A. et al., 2017; Van Leeuwen, Janssen, Erkens, Brekelmans, 2014) raising the need for additional studies to illuminate further the micro-level of use in particular why some teachers choose to make limited or no use of PLA. In this study, we build on our existing line of work (Author A. et al., accepted 1, 2) and propose two new factors as potentially explaining this trend, related to general conceptions of teaching in online settings and digital literacy (Dazo, et al., 2017). One way of tackling the latter is the provision of interactive training workshops that allow for discussions and exchange of ideas amongst teachers. The former is rather more challenging, yet a course- or faculty-wide policy detailing the teachers' obligations in contacting and monitoring students could have been beneficial.

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Tables and figures

Table 1: Themes emerging from thematic analysis

Main themes	**Subthemes**
Existing student support approaches	• Perceptions about teaching online • Contacting students • Monitoring performance and contact
Accessing OUA	• What points during the course presentation OUA is accessed by teachers
OUA features	• VLE data • Predictive data • VLE and predictive data
OUA usefulness	• Specific features of the OUA, • Design of online courses, • Type of students.
OUA challenges	• Selection of OUA features, • Accuracy of predictions, • Access to OUA.
Data literacy	• Understanding of OUA • Training sessions

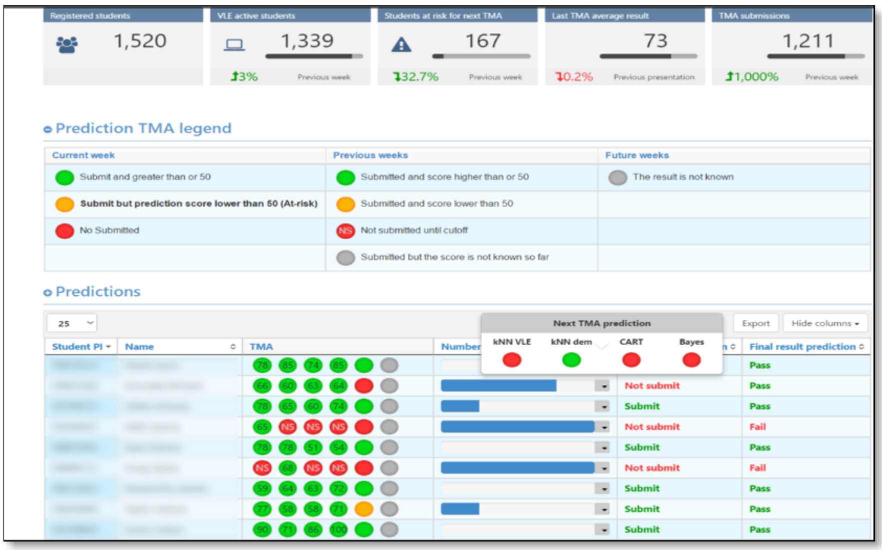


Figure 1: OUA dashboard with VLE and predictions for individual students

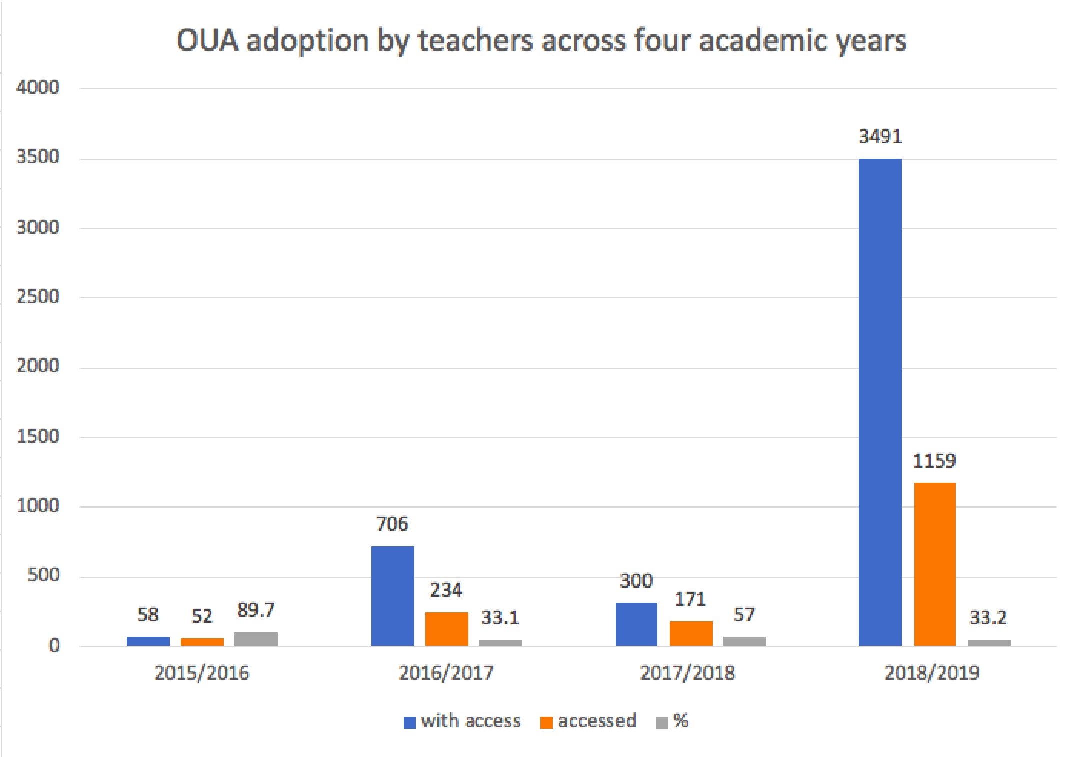
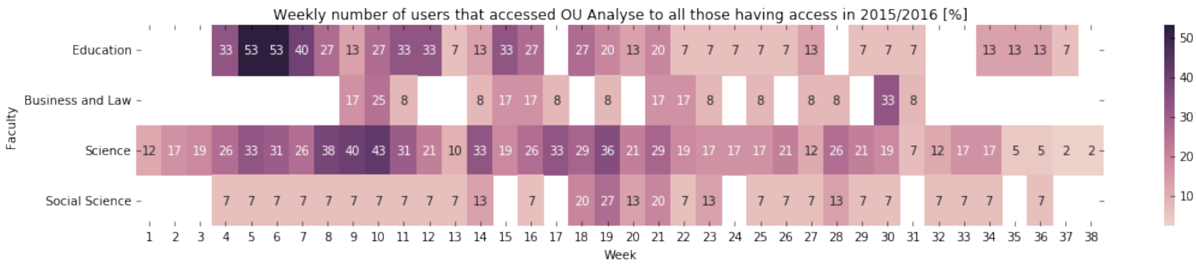
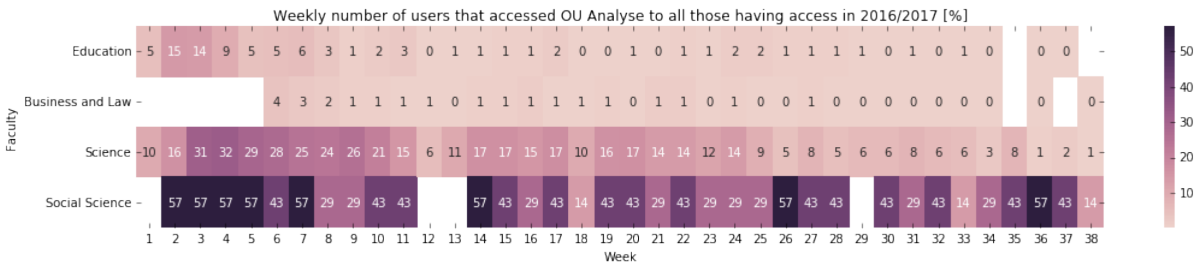


Figure 2. OUA adoption by teachers during the last 4 academic years

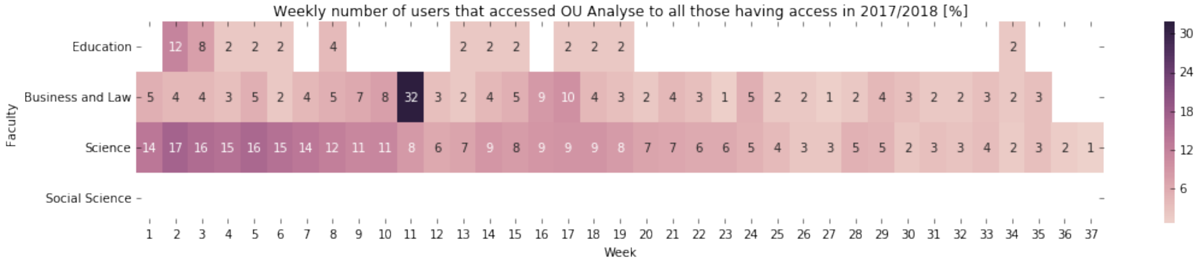
2015/16



2016/17



2017/18



2018/19

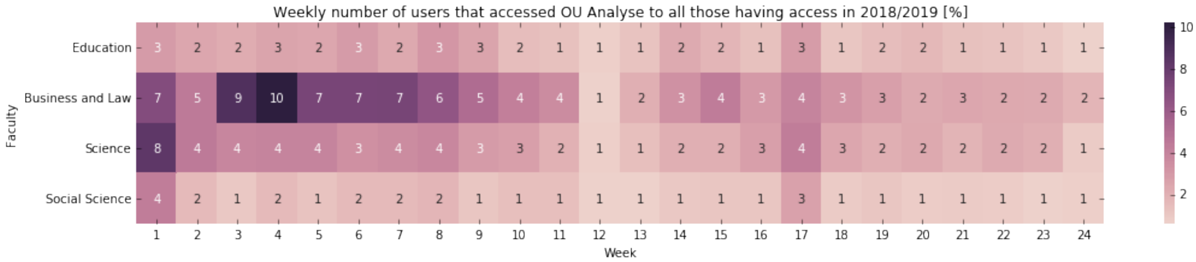


Figure 3-6: Percentage of teachers accessing OUA relative to those teachers with access to OUA per academic year.

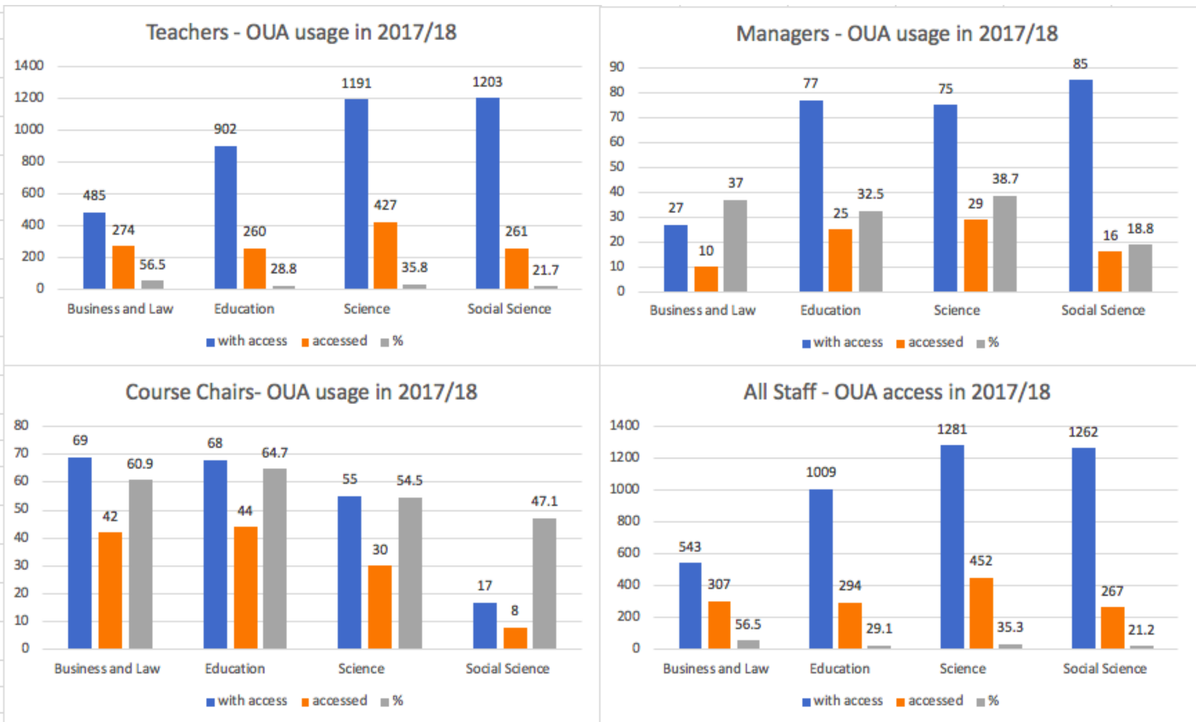


Figure 7 Staff usage of OUA in 2018/19 across four faculties

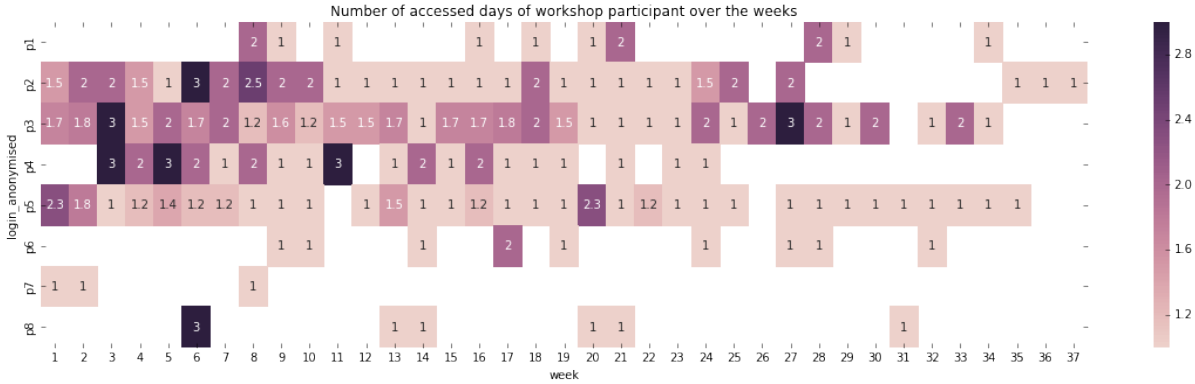


Figure 8: OUA usage by the eight participating teachers.