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Learning analytics in open and distance higher education:

The case of the Open University UK

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The Open University UK

1. Introduction

The availability of online distance learning programmes has seen a sharp increase during the last decade. Technological and communication advances in audio, video and mobile learning and improved student support systems (Sewart, Keegan, Holmberg, 2020) have resulted in an increasing number of higher education institutions, both distance and campus-based, offering online teaching and learning provision. In addition to online courses typically hosted in a Virtual Learning Environment (VLE), lifelong online learning resources are offered through massive open online platforms such as Futurelearn and Coursera, and more recently, through the provision of professional credentials designed to boost in-demand career skills (coined as microcredentials). Yet, online and distance higher education faces several and unique challenges compared to traditional or campus-based education such as the offering of high-quality learning experiences (e.g., Davis, Gough & Taylor, 2019), the lack of an evidence-informed approach to designing learning materials (e.g., Herodotou et al., 2019c) and high student drop-out rates (e.g. Bawa, 2016).

In online and distance learning contexts, learners have been perceived as self-directed, driven by their own personal interests and as individuals who make sense of the world through an inquiry-led approach to learning, that is, through manipulating, testing, observing and questioning (e.g., Bell et al. 2009; Song & Bonk, 2016). Yet, this may not hold true in practice. Transactional distance - the impact of time and distance (psychological, cognitive, affective) on learners' interactions with study material and on their communication with others - may inhibit learning engagement and the achievement of desired learning outcomes (Moore, 1993). In addition, the role of the teacher in supporting learners can be more challenging within online and distance learning settings. A lack of face-to-face interaction can inhibit recognition of learning difficulties and the provision of appropriate support (Crawley, Fewell, & Sugar, 2009). Further, the often-large number of students with whom an online teacher simultaneously interacts may result in limited scaffolding of the learning process and a greater likelihood of students failing or not completing their studies.

Online and distance teaching and learning can be informed and supported by Learning design (LD), that is "a methodology for enabling teachers/designers to make more informed decisions in how they go about designing learning activities and interventions " (Conole, 2012, p. 6). It is structured on socio-cultural theories of learning and emphasizes "active pedagogies" to achieving certain learning objectives and motivate students (Holmes et al., 2019, p.311). Holmes et al. described three complementary approaches to LD: a) the IMS Global's Learning Design Specification emphasizes the importance of learning resources or content (such as templates, instructions, learning objectives) that should be adaptable and sharable, b) the Learning Designer is a framework that categorizes learning activities into, for example, acquisition that is activities requesting to read text or watch a video, or inquiry that is activities such as lab experiments, field trips, simulations and games, and c) the Open University's Learning Design Initiative provides a taxonomy of learning activities (similar to some degree to the Learning Designer) and their anticipated workload. These are: assimilative (reading, watching etc.), finding and handling information (listening, collating etc.), communication (debating, presenting etc), productive (applying, investigating etc.), interactive (trialling, modelling etc) and assessment (writing, critiquing etc.). Despite the significance of such constructivism frameworks to support open and distributed learning, there is a need to develop new theoretical perspectives that will identify how to implement scalable, effective, and personalised online and distance learning experiences (Zhang, Burgos, Dawson, 2019).

Learning analytics have emerged as a promising innovation which could enhance the quality of online and distance higher education and offer learners personalised and responsive learning experiences. Higher education institutions now have the power to leverage historical student information such as engagement in the VLE and library swipes, together with demographic information, and create models that can visualise student learning journeys (e.g., Charleer, et al., 2016) and support learning processes (Ferguson & Shum, 2012; Papamitsiou & Economides, 2014). Learning analytics can empower teachers to provide timely support to students by accessing student performance predictions, enabling them to effectively monitor and support thousands of students (e.g., Herodotou et al, 2019 a; 2019b). Such insights can both inform the design of online courses and qualifications by improving content that students struggle with or do not access often (e.g., Rienties, Boroowa et al., 2016), and address student retention (e.g. Zacharis, 2015).

Despite the promise to revolutionise online learning, the development and adoption of learning analytics in higher education remains low. Several institutions are beginning to explore the use of learning analytics dashboards with students and teachers (e.g., Bodily et al., 2018; Scheffel et al., 2017) and have developed approaches to identify and support, in particular, those students deemed to be at risk of failing (e.g., Calvert, 2014; Herodotou et al., 2019). Yet, these approaches are often described as "early adoption" or implementations at a "small-scale" (Dawson et al., 2018; Ferguson et al., 2016). Very few institutions have developed, tested and adopted learning analytics as their main organisational approach. The Open University (OU) in the UK is one of the first higher education institutions in the world to have enacted a university-wide implementation of learning analytics for its 170,000 distance learning students (Herodotou et al., 2020). In this chapter, we reflect on two major learning analytics initiatives that took place at the OU in the last six years and which facilitated the adoption of analytics across the university: a) *Analytics for Action (A4A)* focused on the use of learning analytics to inform the learning design of online courses (Rienties, Herodotou, Olney, Schencks, Boroowa, 2018) and b) *Early Alert Indicators (EAI)* examined the use of predictive learning analytics in online teaching and their potential to identify students at risk, and informed teachers who can proactively intervene (Herodotou, Rienties, Boroowa, Zdrahal, Hlosta, 2020). We will showcase how each initiative brought up both a different and a shared set of challenges and highlight lessons learnt from their implementation. We aim in particular to illuminate the risks and potential of learning analytics in the unique context of open and distance education that can inform the development of appropriate pedagogical practices, material and assessment and effectively support students' individual learning journeys online.

2. Settings: The Open University (OU) UK

The Open University (OU) is a world leader in modern distance learning and has educated more than two million people worldwide since its launch in 1969. It is now one of the largest universities in Europe (approximately 170,000 students) and a pioneer of teaching, learning and engagement methods that promote educational opportunity and social justice. It defines its mission as "open to people, places, methods and ideas", provides high-quality formal and informal university education to all who wish to realise their ambitions and fulfil their potential. The OU enables students and informal learners to achieve their career and life goals by studying flexibly, at times and places that suit them. The vision of the OU around learning analytics is to use and apply information strategically (through specified indicators) in order to retain students and progress them in order to complete their study goals. The OU was the first institution globally to adopt a policy on the ethical use of student data in learning analytics in 2014. To facilitate this the OU has developed and implemented operational mechanisms for generating and using analytic insights related to increasing student persistence and inserted these into key business cycles. The focus of this activity has been in the following three areas: a) availability of data, b) creation of actionable insight, and c) impact on the student experience. This activity resulted in two major business/research initiatives that spanned six years and enabled the adoption and large-scale implementation of learning analytics across the university.

3. Analytics for Action (A4A)

Analytics for Action (A4A) was a university-wide initiative that focussed on the use of learning analytics to inform the learning design of online courses. It resulted in the development of the Analytics 4 Action (A4A) Evaluation Framework (Rienties et al., 2016a) which provides a comprehensive approach to identifying issues with student performance and progression and embeds these in the course evaluation enacted by student support teams, and course and qualification teams. The framework developed in partnership with academics and learning design practitioners can support the students' experience and learning outcomes during and after a course's completion, and enable the university to monitor the quality of offering and enhancement processes.

The framework is operationalised in the form of the A4A toolkit (see Figure 1). The toolkit enables the real-time monitoring of course performance (see more in Chapter X) on the premise that course leaders will identify and implement interventions to the current/live as well as the next course presentation which might improve teaching and learning quality. Analysis of relevant data can indicate potential interventions that might be made with the aim of improving student engagement and retention. The A4A toolkit covers (a) the types of data that practitioners might review, (b) possible actions that could be taken in response to the data, and (c) methods of evaluating these actions. The process of monitoring of course data is sustained by Learning Designers who provide support to course teams. Support for staff ranges from helping to interrogate data sources (Rienties et al., 2016b) such as student demographics, qualifications profiles, assessment submissions and scores, pass and completion rates, retention, overall engagement with VLE, to identifying potential issues with the course presentation and suggesting remedial actions or interventions to improve performance. Such support takes the form of face-to-face workshops on how to use data tools, face-to-face support meetings as well as drop-in sessions hosted by the learning designers. To prioritise the allocation of the finite A4A support available, faculties are asked to nominate courses that 'need attention'.

As an activity, A4A is now embedded in the institutional Quality Monitoring and Enhancement (QME) Process as one means of improving the quality and delivery of curriculum. In its fourth year (2019-2020) of mainstream activity, there are 46 undergraduate courses participating, with more than 400 teaching staff expected to be trained in the use of available data tools by the end of the current cycle. In a survey conducted in 2018, 91.4% of teachers were satisfied with the training sessions and 87% of faculty staff were satisfied with the data support meetings. A further 76% of participating staff agreed that the meetings had helped them to identify an action that could be taken in their courses in order to improve student outcomes.

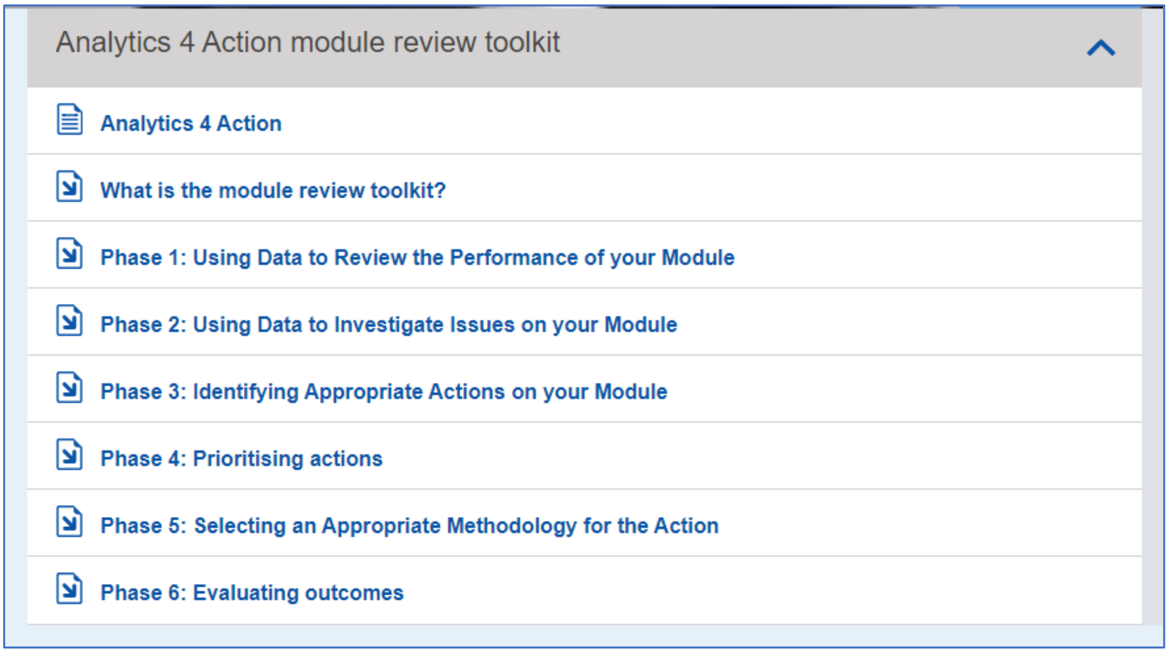
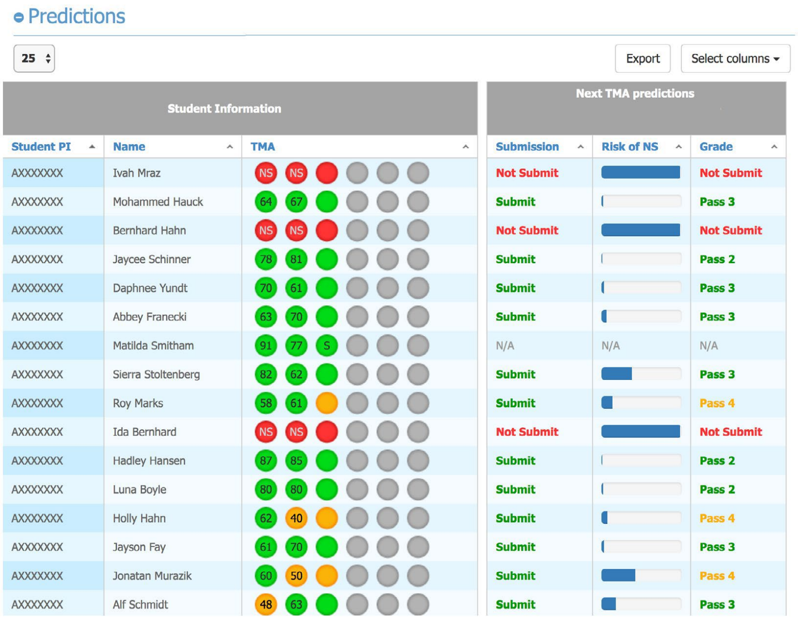


Figure 1. The Analytics for Action (A4A) toolkit

4. Early Alert Indicators (EAI)

The Open University has an 'open entry policy', which means that students can register for study in most of the university courses without requiring any prerequisites e.g., high school certificate. As opposed to filtered entry, open entry policy has much higher student withdrawal rates. To address this challenge, predictive learning analytics (PLAs) indicators were tested at the university to predict student completion and pass rates. These insights were provided to teachers in order to proactively intervene, help and prevent student failure. In particular, OU Analyse (OUA) - a machine-learning predictive system - can produce predictions on a weekly basis as to whether or not students will submit their next teacher-marked assignment and is able to present potential outcomes to teachers in a colour-coded dashboard to prompt action, i.e., proactively support and "save" those students from failing (see Figure 2). Predictions draw from: (a) student demographics, (b) VLE engagement, (c) assessment data, and (d) data from other student engagement and outcomes on a previous presentation of the course. It is worth noting that the university is committed in the ethical use of student data for improving services and better supporting students. The Student Privacy Policy details how student personal data is used by the university including the use of learning analytics for monitoring performance and evaluating teaching (See https://help.open.ac.uk/how-the-ou-uses-student-data).

This is a highly innovative project across the higher education sector; the Higher Education Commission (2016) recognised the OU as the only institution that has made a significant headway in using predictive analytics (via OUA) in its practices. OUA is one of the few analytics systems available in the world that has been tested and now rolled into business as usual across the university. Its systematic evaluation has shown that its use can improve student learning (performance and completion) on a large scale (Herodotou et al., 2020). What is particularly inspiring is that a forecast of future performance gives teachers actionable insights to provide timely support and enable students to succeed. Several small-scale pilots took place before 2018 through which the algorithms behind OUA were refined and the dashboard was tested with a small sample of teachers. A university-wide implementation took place in 2019 for which the performance of 161,261 students was predicted on 530 courses with 1,774 teachers (offer refer to as "tutors" or "Associated Lecturers") recorded as using OUA. OUA is now accessible via the teachers' homepage allowing any teacher across the university to get access to student predictions.



Student Information			Next TMA predictions		
Student PI	Name	TMA	Submission	Risk of NS	Grade
AXXXXXXX	Ivah Mraz	NS NS	Not Submit		Not Submit
AXXXXXXX	Mohammed Hauck	64 67	Submit		Pass 3
AXXXXXXX	Bernhard Hahn	NS NS	Not Submit		Not Submit
AXXXXXXX	Jaycee Schinner	78 81	Submit		Pass 2
AXXXXXXX	Daphnee Yundt	70 61	Submit		Pass 3
AXXXXXXX	Abbey Franecki	63 70	Submit		Pass 3
AXXXXXXX	Matilda Smitham	91 77 S	N/A	N/A	N/A
AXXXXXXX	Sierra Stoltenberg	82 62	Submit		Pass 3
AXXXXXXX	Roy Marks	58 61	Submit		Pass 4
AXXXXXXX	Ida Bernhard	NS NS	Not Submit		Not Submit
AXXXXXXX	Hadley Hansen	87 85	Submit		Pass 2
AXXXXXXX	Luna Boyle	80 80	Submit		Pass 2
AXXXXXXX	Holly Hahn	62 40	Submit		Pass 4
AXXXXXXX	Jayson Fay	61 70	Submit		Pass 3
AXXXXXXX	Jonatan Murazik	60 50	Submit		Pass 4
AXXXXXXX	Alf Schmidt	48 63	Submit		Pass 3

Figure 2: The OU Analyse dashboard predicting students at risk of failing (note that the names are nor real)

Student predictions are automated so that new machine learning models are generated automatically every week, providing quality checks and highlighting shifts or any other changes in the student performance data. In addition to providing direct support to teachers, the university is piloting a new version of the dashboard with students with personalised study recommendations, with the aim of enhancing the student-teacher interaction in online and distance higher education. Rigorous evaluation has shown that (a) systematic use of OUA by teachers is the second most significant predictor of student course completion and pass rates (the first being best previous student performance) (Herodotou et al., 2019a); (b) OUA complements and enhances the teaching practice by encouraging teachers to be more proactive and supportive of students; further, OUA is shown to contribute to teachers' professional development and capacity of supporting students at risk (Herodotou et al., 2019a), (c) better student learning outcomes are recorded, the more teachers make use of the system (Herodotou et al., 2019b); (d) teachers had better student outcomes the academic year they were accessing OUA than in previous years when they had no access to it (Herodotou et al., 2019b). Some illuminating quotes from teachers who used OUA state that: *"I had a difficult group this year and without OUA, I think I would have lost around 4-5 of them but all of them made it till the end and passed"*. Another teacher explained: *"One of the things that OUA a hundred per cent has made me do is being much more proactive in sending messages [to students] between assignments. I sort of feel that I am on top of what the students are doing."*

An example of how a teacher successfully used the dashboard is discussed below. This teacher was able to use the dashboard to provide timely support to a female engineering student from a Black and Minority Ethnic (BME) background with no prior higher education experience, and enable her to succeed. Prior to this, the student received 100% on the first assignment (a quiz) and 86% on her second assignment. However, in week 10 (see Figure 3), the OUA flagged the student as unlikely to submit the third assignment. Upon further inspection by the teacher, it became apparent that the student had not accessed the VLE after submitting the previous assignment three weeks earlier. When the teacher contacted the student, it became apparent that the student's lack of activity on the VLE was due to the birth of her third child. While registering for the course, the student had not disclosed her pregnancy as she was not sure whether the university would allow her to carry on with her studies. Not only did the teacher resolve the misunderstanding, but also provided support that enabled her to get back on track with her studies. Subsequent monitoring of the student's performance helped the teacher identify another occasion when the student had limited VLE activity (weeks 15-17 in the screenshot below) and was likely to fail to submit her next assignment. Again, the teacher was able to prevent the student from giving up on her studies by identifying the problem she was facing and providing timely support. The student eventually completed the course with an average score of over 80%.

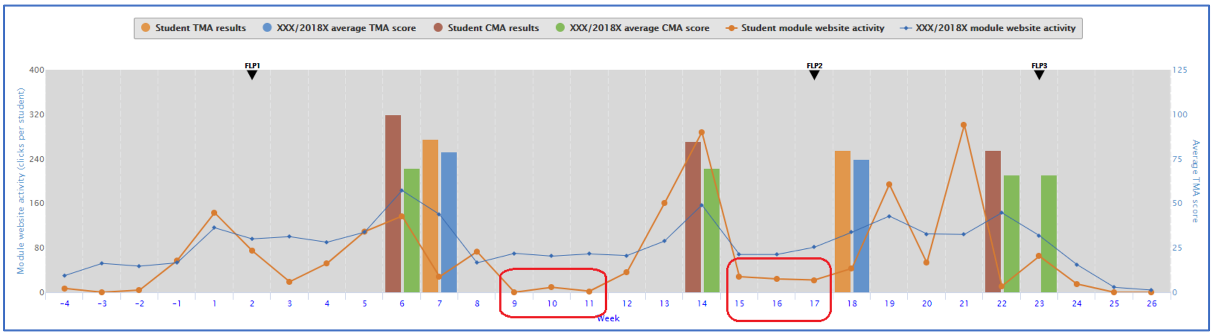


Figure 3: The activity of a student in OUA. Highlighted are periods of low engagement with the course.

5. Lessons learnt from the implementation of learning analytics at the Open University UK

As part of the evaluation of the uptake of predictive analytics across the university, the authors had previously proposed a set of practical recommendations (See Figure 4) around the implementation of predictive learning analytics (PLAs) in open and distance education. Figure 4 summarises early guidelines developed as a result of 20 in-depth interviews with stakeholders involved in the application of PLAs at the OU. These guidelines suggest that the success of a PLAs implementation relies on the careful consideration of a variety of factors including stakeholders' multiple perspectives and time availability, research and provision of evidence of impact, and sustained communication.

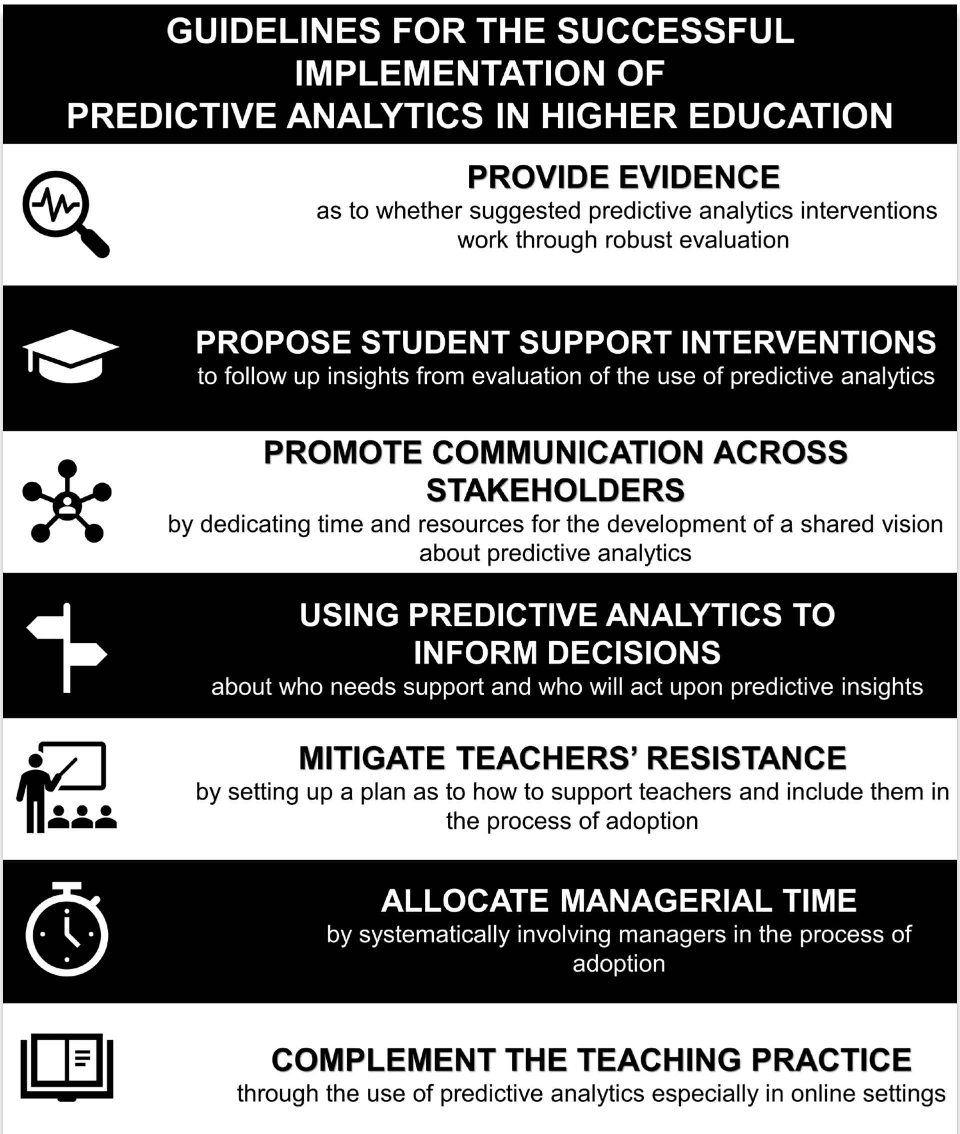


Figure 4: Guidelines for the implementation of PLAs at the Open University UK (from Herodotou, Rienties, Verdin, Boroowa, 2019)

As a result of the experience gained at the OU, several further aspects have been identified which potentially influence the success of learning analytics initiatives at different levels of implementation. Table 1 summaries the key elements and the lessons learned. In summary, the key elements fall under four main headings, and it is recommended that these are considered by other online and distance learning institutions preparing to successfully implement learning analytics initiatives:

(a) **Clarity of vision:** a clear and measurable understanding of the project objectives and direction is needed to ensure that all stakeholders understand the scope of the activity and have expressed, discussed and resolved any conflicting perspectives. A clear plan should be developed detailing the project objectives and timeline, the process through which these can be achieved and measured, potential barriers and mitigation strategies.

(b) **Consideration of ethical perspectives:** Any concerns or opposing perspectives should be identified and addressed from the start of the project to ensure that relevant challenges faced elsewhere (in other organisations or settings) have been discussed and solutions identified. Special attention should be given to the ethical dimension of the implementation ensuring that student interests and welfare are safeguarded.

(c) **Institutional readiness**: A good understanding of the readiness of the institution to adopt and implement analytics can assist in engaging different stakeholders with project activities. In particular, (i) other unrelated or conflicting organisational change may have an impact on stakeholders' willingness to engage and commit themselves and derail or delay the activity, (ii) technical requirements should be considered to ensure that the needed infrastructure is in place (e.g., data warehouse), and (iii) an understanding of staff readiness in terms of digital and data literacy skills, as well as technical expertise should inform relevant support such as training on the use of new tools.

(d) **PLAs specific considerations**: A set of concerns or barriers were flagged throughout the implementation, in particular (i) PLAs were perceived as a sort of 'self-fulfilling prophecy' which might potentially de-motivate and impact on interactions between students and teachers. Our response to that was to clarify the objective behind PLAs which is the timely identification of students at risk and the provision of appropriate support in order to support students and help them to succeed. We also pointed to evidence of impact showing that teachers who acted upon PLAs were more likely to have better student performance, and this improvement was not related to more engaged teachers in general; and (ii) stakeholders were often concerned about additional workload for teachers when using PLAs. We managed to debunk this myth by exploring and comparing non-PLAs support practices to PLA support practices. Evidence suggested that student monitoring without PLAs is typically much harder in practice, being more time-consuming and less systematic, and being associated with greater risk of not effectively detecting students likely to need support.

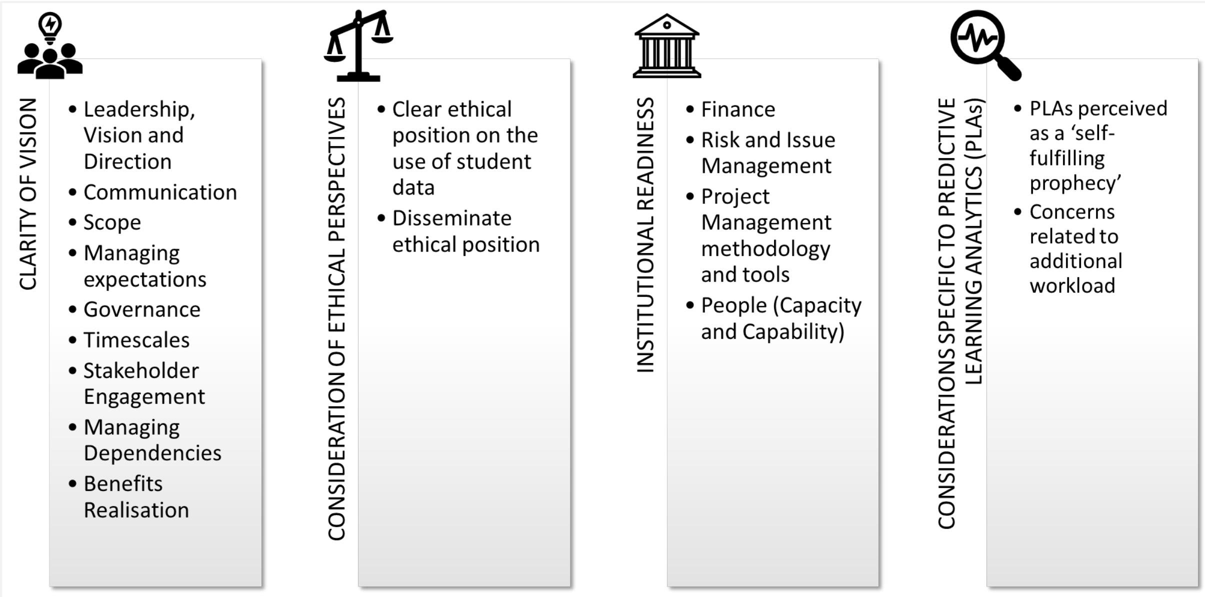


Figure 5: Areas of consideration for the implementation of learning analytics based on lessons learnt at the Open University UK

6. Conclusions

In this chapter, we showcased that the process of implementing learning analytics in open and distance higher education is not a straightforward one. It is rather complex and dynamic involving varied stakeholders with varied expectations, roles, and responsibilities across the different levels of an institution. We reflected in particular on our extensive experience, spanning the last six years of using analytics with online teachers at the Open University (OU) UK and commented on the conditions that can both help minimise obstacles such as teachers' resistance to change, and promote the adoption of new analytical outputs and technology.

We presented and compared insights from the implementation of two university-wide initiatives, the first focusing on the use of learning analytics to inform learning design, and the second examining the use of predictive learning analytics to identify students potentially at risk and facilitate proactive interventions. The OU has achieved significant progress in testing, implementing and widely adopting an evidence-based approach to learning analytics that could inform practices in other open and distance higher education institutions. Yet, this is not to say that no challenges remain. Further issues to consider is the scalable implementation of approaches such as predictive learning analytics especially when there are no resources available to employ teachers that will communicate with students and moderate timely interventions. Models of peer learning and support could be put in place to support and solve "common" learning difficulties while an escalation process would allow for major issues to be dealt by teachers and student support teams. We would like to close this chapter noting the importance of human interaction to facilitate and achieve learning outcomes, and which with appropriate technological support (such as predictive systems) would enable teachers to focus their time and effort on those students in most need for support and contribute to the sustainable application of such models across higher education.

Table 1: Key elements in the successful implementation of analytics at the Open University UK

CLARITY OF VISION	
LEADERSHIP, VISION AND DIRECTION	**Role of the project sponsor:** The project sponsor needs to always be visibly behind the project and be the point of escalation, when needed, in order to quickly resolve problems. It is important to have a sponsor who has a great understanding of the project and where it needs to go. Additionally, this person should be the champion for the project where possible.
COMMUNICATION	**Communicating with clarity and purpose:** There is a need to determine the aim of each communication and being clear what the goals of the project are. Additionally, it is important to be clear what is being circulated for good practice as opposed to what is mandatory. If it is mandatory, it is also important to ensure that all management layers are in support of this and understand and can articulate the reason for it. **Specialist skills:** The project team struggled initially with tailoring messages to stakeholders. A communications specialist would have known how to adapt comms to the various stakeholders, and indeed ensured that the right questions were asked about why the comms was needed.
SCOPE	**Purpose of the project:** In order to avoid confusion amongst stakeholders and prevent wastage of time, inclusion of non-strategically funded business as usual (BAU) tasks needs to be considered, if at all avoided. If the project did not contain any BAU tasks, then all time and budget would be appropriately used for those strategic priority tasks only. **Change of scope:** The scope of any long-term, multi-year project is likely to change several times. Indeed, this is appropriate in order to deliver what is needed as requirements can evolve. There were several conflicting priorities which could change regularly based on the priorities of the university. Agile methodology allows for iterative release, which can aid delivering something to see what works and amend as necessary. In a rapidly changing environment, the switch to using agile methodologies meant the project team found it easier to introduce alterations and changes in priorities. **Delivery and handover:** The tools have been developed through the Analytics Project were instrumental to successfully realise pedagogical benefits. It is important that the use of new tools is embedded in normal working practices.
MANAGING EXPECTATIONS RELATED TO OUTPUT	Increased involvement of end-users (teachers) at an early stage to feed into reporting requirements and specification to ensure that output provided meets expectations. Additionally, ensuring that when analytics data/information is provided to users that it comes with guidance that sets expectations of what actions can be taken from it. It is important for work to be being part of or aligned to existing processes where possible to avoid the perception (or actual) of duplication of effort.
GOVERNANCE	We had the ability to change membership and responsibility of the governance groups. Keeping the membership of these groups fluid, meant membership changed as needed through the stages of the project, but with this it is important to ensure the Terms of Reference are updated accordingly and that the group signs up to this in order to ensure effectiveness of working.
TIMESCALES	We came across a slower than expected uptake of Analytics due to the length of time to undertake culture change, particularly when there is resistance. It may have been more appropriate to plan and execute the project in phases, to take account of the extent of culture change needed. However, this would require trust from senior management in approving a project business case with less detail in the outline project plan.

STAKEHOLDER ENGAGEMENT	**Clarity of purpose, roles and responsibilities:** There was confusion at the beginning on what the project incorporated and which departments we were working with. We encountered a perpetual perception that the project was somehow separate from the staff in partner units who were contributing to the project. Don't assume that people talk to each other or disseminate information even when asked. We should have made sure that we had faculty engagement earlier on in the project. A need for much clearer communication about who is working on a project and buy-in from those on the project to be consistent in their description of the project. **Prepare the ground for Cultural Change:** A lot of the work we needed to achieve involved a significant shift in culture. At the beginning of the project we should have had a workshop to identify group formation dynamics and have a change management specialist there to provide tools for the team when faced with the challenges associated with culture change. **Use success stories to engage and develop champions:** Where possible identify and involve champions (or skeptic you can convert) in work and produce case studies for what worked well. Use success stories or case studies which outline best practice; what has happened and what has resulted from it; and start developing these as early as possible to get further champions onboard and to reassure stakeholders.
MANAGING DEPENDENCIES	There was a disconnect between priority levels between two dependent pieces of work which complicated discussions over resourcing. Ensure that dependent projects/pieces of work have the same priority to ensure that neither is delayed or negatively impacted in some way by the other.
BENEFITS REALISATION	**Advantages**: A lot of time was spent on benefits mapping through a detailed institutional process, which was perhaps overcomplicated. That said, having the benefits mapped proved useful on many subsequent occasions including prioritisation of tasks within the project when there were insufficient resources of time, people or money. **Limitations**: The project was an enabler to provide Faculties with the data and/or tools for them to make changes. This meant that the business impact was difficult to articulate. In addition, the project team did not have any influence over the scale and scope of the changes made by each faculty. As such, it was difficult to measure cost benefits of the project. A recognition of enabling project, direct and indirect benefits would also be helpful.
CONSIDERATION OF ETHICAL PERSPECTIVES	
CLEAR ETHICAL POSITION ON THE USE OF STUDENT DATA	As part of the project, the institution developed the Policy on the Ethical use of Student Data for Learning Analytics, which clearly stated the University's intentions around the use of student data. The policy was developed in consultation with staff and students.
DISSEMINATE ETHICAL POSITION	Merely publishing a policy on how an institution intends to ethically use student data is not enough. As an institution, we needed to communicate that the policy exists. This is in line with the GDPR requirements around transparency.
INSTITUTIONAL READINESS	
FINANCE	**Recruitment**: The project was constrained by budget planning. Staff could only begin to be recruited following budgetary sign-offs, which meant some staff had shorter contracts, or that we needed to spend more budget initially on contract staff until fixed-term staff started. Consider the implications of financial year budget cycles in project start-up and close down phases.

RISK AND ISSUE MANAGEMENT	Risks and issues were managed in the project management team which were dealt with or escalated as required. We fully utilized the project management team which aided rather than resisted our ability to control the project.
PROJECT MANAGEMENT METHODOLOGY AND TOOLS	A lot of time was spent over-working what would be delivered as part of the project and providing paperwork. Keep paperwork to a minimum, adopt Agile Methodology to allow for agility in scope of the project.
PEOPLE (CAPACITY AND CAPABILITY)	Try to limit complications such as moving staff/projects between programmes and departments. **Subject matter expertise:** We made the decision to pay several teachers for the work they did on the project which was invaluable contribution to our work. It is essential to involve teachers in this type of work, as it was felt without this, you would not see the pedagogical benefit. However, it does need to be understood that paying teachers to be involved in research activities can possibly bias the results, either negatively or positively due to some teacher voices been heard more than others.
CONSIDERATIONS SPECIFIC TO PREDICTIVE LEARNING ANALYTICS (PLAs)	
PLAs PERCEIVED AS A 'SELF-FULFILLING PROPHECY'	Clarify the objective behind PLAs which is the timely identification of students at risk and the provision of appropriate support in order to support students and help them to succeed.
CONCERNS RELATED TO ADDITIONAL WORKLOAD	Debunk myth by exploring and comparing non-PLAs support practices to PLA support practices.

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