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Predictive Learning Analytics "At Scale": Towards Guidelines to Successful Implementation in Higher Education Based on the Case of the Open University UK

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Abstract

Predictive Learning Analytics (PLA) aim to improve learning by identifying students at risk of failing their studies. Yet, little is known about how best to integrate and scaffold PLA initiatives into higher education institutions. Towards this end, it becomes essential to capture and analyze the perceptions of relevant educational stakeholders (i.e., managers, teachers, students) about PLA. This paper presents an "at scale" implementation of PLA at a distance learning higher education institution and details, in particular, the perspectives of 20 educational managers involved in the implementation. It concludes with a set of recommendations about how best to adopt and apply large-scale PLA initiatives in higher education.

Notes for Practice (research paper)

- The uptake and integration of learning analytics in most higher education institutions is limited, requiring knowledge about how to implement PLA at scale.
- Analysis of the perspectives of 20 educational stakeholders about the adoption of PLA at the Open University UK led to a set of recommendations about how to overcome resistance and implement PLA in higher education.
- The proposed set of guidelines needs to be tested in a variety of contexts, including campus-based universities and other distance learning institutions.
- Further research is needed to understand and overcome teacher resistance to using PLA in higher education.

Keywords

Predictive learning analytics, higher education, distance education, management, guidelines, adoption.

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1. Introduction

In this paper, we aim to identify how Predictive Learning Analytics (PLA) can be effectively adopted and integrated in distance learning educational contexts for an enhanced learning experience. As argued by Nyce (2007), PLA makes use of "a variety of statistical and analytical techniques to develop models that predict future events or behaviours" (p. 1). PLA includes various tools used to identify which students are likely to pass a course, and which are at-risk of failure (Calvert, Strong, & Gallagher, 2005; Gašević, Dawson, Rogers, & Gasevic, 2016; Kovanović et al., 2015; Tempelaar, Rienties, Mittelmeier, & Nguyen, 2017). However, as highlighted during the recent LAK '18 conference (Dawson et al., 2018), yet relatively underexplored are the perceptions of relevant educational stakeholders in relation to using PLA to support learning and how these could inform the future implementation of PLA at scale across higher education (HE) institutions. Three major stakeholders are involved in PLA implementation: 1) teachers who make use of PLA insights to intervene and support students, 2) students who either have direct access to performance predictors through PLA or receive PLA interventions initiated by their teachers, and 3) educational managers in charge of evaluating and implementing PLA initiatives across institutions. While a body of literature presents evidence about the important role teachers have in driving the learning process and supporting students at risk, including our own previous work on the uptake of PLA by teachers (Herodotou et al., 2017; Rienties, Herodotou, Olney, Schencks, Boroowa, 2018; Shea, Sau, & Pickett, 2006; Arbaugh, 2014; Li, Marsh, Rienties, & Whitelock, 2017; Nguyen, Rienties, Toetenel, Ferguson, & Whitelock, 2017), little is known about how the other two groups of major stakeholders perceive PLA and its adoption in HE. This paper examines in particular the perspectives of educational managers involved in PLA implementation at a distance learning HE institution.

As summarized in two recent reviews about the uptake of learning analytics and more specifically PLA (Ferguson & Clow, 2017; Rienties, Cross, & Zdrahal, 2016), the actual uptake and integration of learning analytics in most institutions is rather limited. These trends raise the need to unpack how PLA is perceived by different stakeholders within HE, and to identify the factors that may encourage or inhibit wider adoption of PLA. Understanding the perceptions of involved stakeholders can bring to light issues that potentially prohibit the wider adoption of PLA, and in particular identify ways in which organizational culture is resistant or unwilling to change. Such knowledge can inform the design of PLA initiatives in HE and provide guidelines as to how to introduce, adapt, and facilitate PLA adoption in HE with best possible outcomes for teaching and learning. Recently, Dawson et al. (2018) noted the importance of key conceptual models of adoption that could inform our understanding of the implementation process. Through the lens of Complexity Leadership Theory, they studied learning analytics adoption by interviewing 32 senior leaders (i.e., Vice-Chancellors, DVS) at Australian universities, and found that institutions followed either a top-down instrumental approach to adoption, or an emergent innovators bottom-up approach through a strong consultation process. Most institutions were found to have limited adoption of learning analytics and used them on a small scale. This study, therefore, aims to unpack the experiences of 20 stakeholders who have used two distinct PLA tools (i.e., Student Probability Model, OU Analyse) for the last two years at a distance learning educational institution that has adopted PLA en masse, namely the Open University UK. Through individual semi-structured interviews, this study aims to answer the following Research Questions (RQs):

RQ1: What are the individual perceptions of 20 educational managers within a distance learning HE institution about the adoption of PLA in the organization?

RQ2: What are the challenges that may inhibit wider adoption of PLA across the institution?

Drawing on these results, the study then examines the implications for the design and large-scale implementation of PLA at the Open University UK.

Aligning with Dawson et al. (2018), we adopted “resistance to change” as a key conceptual framework that can inform our understanding of the adoption process. In the next sections, we briefly describe this framework, the two PLA tools adopted across the institution under study, the methodological design of the study, outcomes, and implications for practice.

2. Theoretical Perspectives

Resistance to change (Coetsee, 1993; Piderit, 2000) is one potentially useful conceptual approach for contextualizing and understanding PLA adoption across organizations and individuals. A change will bring up resistance when perceived by individuals as threatening the status quo, i.e., one’s control, routines, habits, traditions, and relationships (Wolfram Cox, 1997). In this respect, it becomes essential for change to be perceived as desirable in order to be supported rather than opposed. The role of managers is referenced in the relevant literature as being critical, as they are the actors formulating the change intentions and soliciting support from the “work floor” (Sillince, 1999). Individual dispositions such as motivation and willingness to change, interactions in the social network within which individuals function, as well as characteristics of the economic environment can determine whether an individual will be supportive or not of change and whether change will eventually happen (Macrì, Tagliaventi, & Bertolotti, 2002).

Higher education (HE) is often characterized by resistance to change, which is commonly linked to organizational culture (Chandler, 2013; Lane et al., 2010; Rienties, 2014). Strong traditions and expectations by staff with longstanding positions characterize HE culture (Chandler, 2013). Change often happens at the organizational level, but may not be endorsed and supported at the individual level. Yet, resistance can be found at both the organizational and the individual level and explained by factors such as poor communication, resource allocation, and staff contracts (Dawson et al., 2018; Coetsee, 1993; Piderit, 2000). One way to facilitate change and tackle resistance is to initiate and harness support from both the senior management and the work floor. For instance, one study at a distance learning institution showed that working with teachers for a sustained period helped them become more comfortable using learning analytics data (Rienties, Boroowa et al., 2016).

At the same time, senior buy-in for organizational change is needed to integrate PLA successfully into daily practice. For example, a large-scale study with 702 teachers at 51 schools (Moolenaar, Daly, & Sleegers, 2010) identified that the role and position of the principal (i.e., senior manager) significantly influenced the transformational leadership and innovative climate. Similarly, in a large-scale medical study of four institutions highlighted that uptake of a new medical procedure was primarily dependent on whether or not the lead clinical supervisor adopted this approach (Jippes et al., 2013). In this paper, we aim to unpack the perspectives of management (senior management, student engagement, tuition delivery, student support) involved in the use of PLA in order to understand how individual and organizational perceptions towards change and innovation influenced adoption and wider implementation of PLA at the Open University UK.

2.1. Two Predictive Analytics Approaches

The present study took place at a distance learning HE institution, the Open University UK (OU), where two distinct PLA systems are used, namely the Student Probability Model (SPM) and OU Analyse (OUA). Both systems were developed organically over the last few years as a response to developing more predictive insights into complex student journeys. These two systems have distinctly different underlying goals and principles; the SPM was initially developed to better forecast the financial implications of how many students would still be studying at the next payment point across all courses at the OU. In contrast, OUA was primarily developed for teachers on an individual course to help them determine which students might be at risk on a week-by-week basis. Following Ferguson (2012), although both systems could be considered as PLA, SPM would be better characterized as an "academic analytics" approach — that is, an approach that can bring change on the political level nationally and internationally — while OUA is a more traditional "learning analytics" approach that can optimize the online learning experience.

2.1.1. The Student Probability Model

The Student Probability Model (SPM) predicts whether an individual student will reach specific milestones (different points in a course presentation or between courses), such as completing and passing a course or returning in the next academic year (Calvert, 2014), as well as how many students are likely to be present at the next milestone (see Figure 1). Predictions in the SPM are based on models generated through logistic regressions of a set of explanatory variables grouped in the following areas:

- Student factors (IMD area, price area, disability, etc.)
- Previous studies (highest qualification on entry, etc.)
- Student course (total credits studying in a year, late registration, etc.)
- Previous progress at the university (best previous score, number of fails, etc.)
- Course and qualification variables

SPM categorizes students into bands based on their probability of achieving specific course milestones (e.g., passing the course). SPM has been piloted with student support services using student bands to inform the application of support interventions (e.g., phone call, email, text) targeting students at risk of falling.

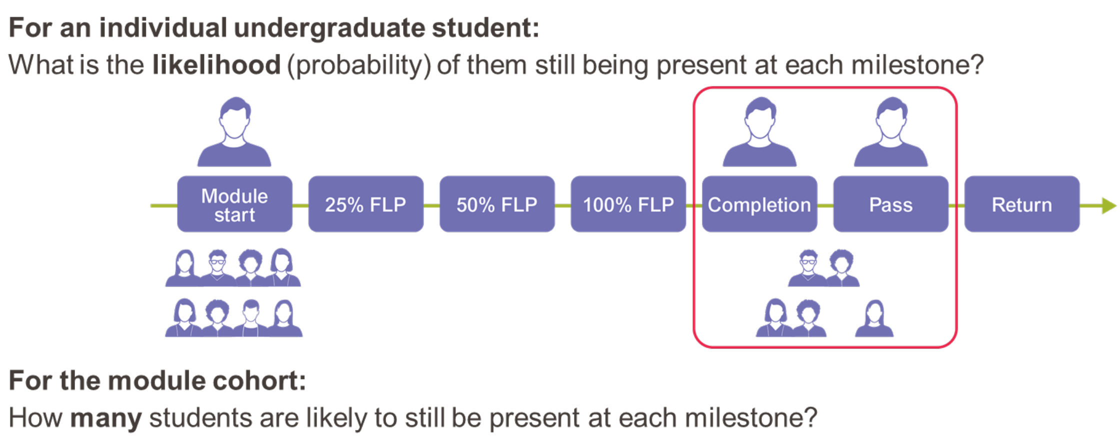
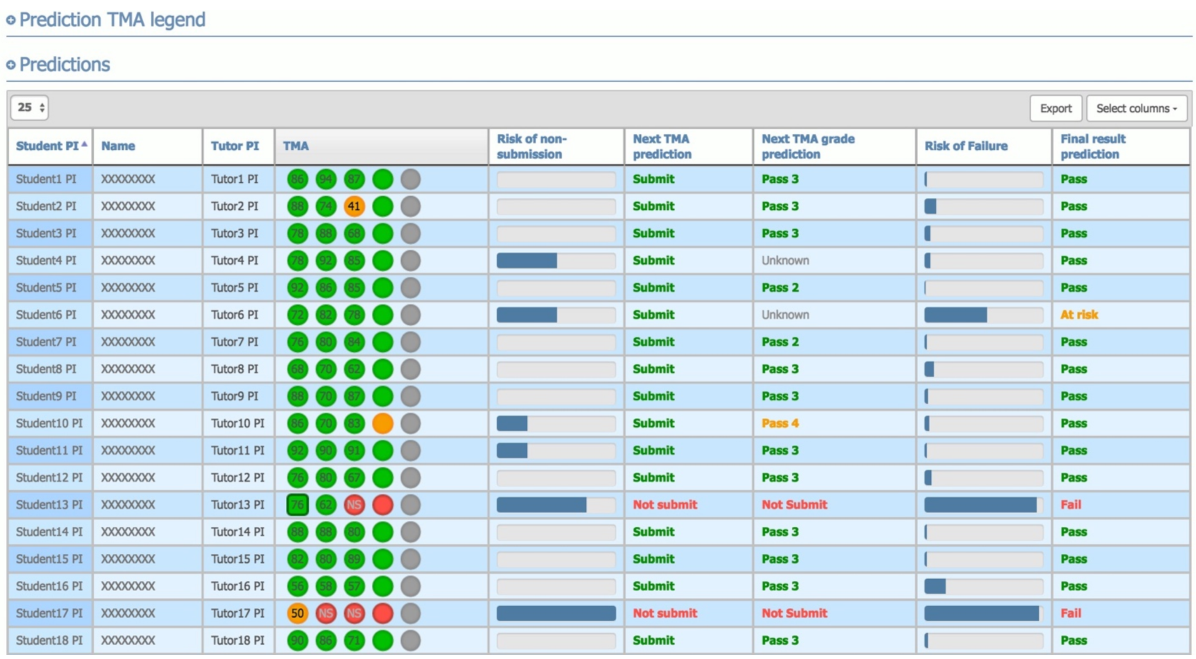


Figure 1: The Student Probability Model (SPM) predicting whether students will reach specific course milestones.

2.1.2. OU Analyse

OU Analyse (OUA) is used to identify learners at risk of failing their studies. OUA predicts, on a weekly basis, whether a given student will submit their next teacher-marked assignment or not. It also uses a traffic light system to pinpoint students at risk (red), those with a moderate probability of failing (amber), and those unlikely to fail (green; see Figure 2). The validity, accuracy, and recall of OUA has been widely tested with 45,000 students and across 40+ modules (Hlosta, Zdrahal, & Zendulka, 2017; Huptych, Bohuslavek, Hlosta, & Zdrahal, 2017; Wolff, Zdrahal, Nikolov, & Pantucek, 2013). OUA has been piloted with more than 500 teachers and 20 online courses in two consecutive studies, with evidence suggesting that systematic use of PLA by teachers can enhance student performance and retention (Herodotou, Rienties, Boroowa, Zdrahal, Hlosta, under review). Interviews with teachers who used the system revealed that PLA could complement teaching practice and systematize how teachers monitor and record online student behaviour. However, the level of adoption and use of the system by teachers remained relatively low, with only 20% of participating teachers making some or systematic use of predictions throughout a course presentation. Even after incentives were offered to teachers, participation remained low. This trend raises the need to unpack how PLA is perceived by different stakeholders within the institution and identify the factors that inhibit adoption and use of PLA for the benefit of student learning and performance.


Prediction TMA legend

Predictions

25 | Export | Select columns

Student PI	Name	Tutor PI	TMA	Risk of non-submission	Next TMA prediction	Next TMA grade prediction	Risk of Failure	Final result prediction
Student1 PI	XXXXXXXX	Tutor1 PI	86 94 87		Submit	Pass 3		Pass
Student2 PI	XXXXXXXX	Tutor2 PI	88 74 41		Submit	Pass 3		Pass
Student3 PI	XXXXXXXX	Tutor3 PI	78 88 68		Submit	Pass 3		Pass
Student4 PI	XXXXXXXX	Tutor4 PI	78 92 85		Submit	Unknown		Pass
Student5 PI	XXXXXXXX	Tutor5 PI	92 86 85		Submit	Pass 2		Pass
Student6 PI	XXXXXXXX	Tutor6 PI	72 82 78		Submit	Unknown		At risk
Student7 PI	XXXXXXXX	Tutor7 PI	76 80 84		Submit	Pass 2		Pass
Student8 PI	XXXXXXXX	Tutor8 PI	68 70 62		Submit	Pass 3		Pass
Student9 PI	XXXXXXXX	Tutor9 PI	88 70 87		Submit	Pass 3		Pass
Student10 PI	XXXXXXXX	Tutor10 PI	86 70 83		Submit	Pass 4		Pass
Student11 PI	XXXXXXXX	Tutor11 PI	92 90 91		Submit	Pass 3		Pass
Student12 PI	XXXXXXXX	Tutor12 PI	76 80 67		Submit	Pass 3		Pass
Student13 PI	XXXXXXXX	Tutor13 PI	76 62 NS		Not submit	Not Submit		Fail
Student14 PI	XXXXXXXX	Tutor14 PI	88 88 80		Submit	Pass 3		Pass
Student15 PI	XXXXXXXX	Tutor15 PI	82 80 89		Submit	Pass 3		Pass
Student16 PI	XXXXXXXX	Tutor16 PI	56 58 57		Submit	Pass 3		Pass
Student17 PI	XXXXXXXX	Tutor17 PI	50 NS NS		Not submit	Not Submit		Fail
Student18 PI	XXXXXXXX	Tutor18 PI	90 86 71		Submit	Pass 3		Pass

Figure 2: A screenshot from OUA showing individual students, the risk of not submitting an assignment, and the probability of passing or failing a course.

3. METHODOLOGY

3.1. Context

This study took place at the Open University UK, a distance learning institution with an open-entry policy — the largest one in the UK with around 150,000 student registrations. Typically, teams of academics and learning design specialists develop OU courses; a teacher supports each student enrolled, working with a group of around 20 students. Typically, these teachers are specialists from outside the institution specifically hired for a particular period and for specific courses. As is common at many distance learning universities, students typically vary considerably in age, with 25% under 25 years old, 36% aged 26–35, 21% aged 36–45, 12% aged 45–55, and 6% aged 56 and over. More than half of them (52%) are working full-time, while 19% are working part-time, 8% are looking after the home/family, and 6% are unemployed and looking for a job. The majority of these students are from the UK (96%), and declare their ethnicity as “white” (87%). Large variations in previous qualifications are typically found across OU courses, making the use of PLA particularly attractive given the strong heterogeneity of prior knowledge.

3.2. Methods

Semi-structured individual interviews were conducted in order to unpack the perceptions of stakeholders regarding PLA, and the challenges involved in its wider adoption across the university. Semi-structured interviews were deemed an appropriate method of data collection due to allowing for the in-depth exploration of a relatively unknown phenomenon by raising questions and prompting follow-up elaboration on answers. Twenty (N=20) semi-structured individual interviews with staff from across the university — representing roles in senior management (x6), student engagement (x4), tuition delivery (x6), and student support (x4) — were conducted by one trained interviewer. The interviewees were purposefully sampled and selected as key stakeholders involved in the use of both SPM and OUA across the university. Participants’ understanding of

PLA was assumed, as they were all familiar with either SPM or OUA. Interviews were face-to-face and took place in August 2017 subject to participant availability. The interviewees included representatives from the following departments and professional functions: Science faculty (x4), Business faculty (x5), Education faculty (x2), Student Support Team (x4), Learning and Teaching Unit (x3), and Human Resources and Strategy Office (x2).

Interview questions were grouped around four topics: vision, strategic alignment, stakeholder engagement, and operational readiness. Key questions included the following:

1. What do you understand as the vision and purpose of [a specific PLA] activity?
2. How does this activity align with the organizational strategy for students?
3. Are you an advocate for this activity? If not why not? If so, why is that?
4. What are the barriers to being able to embed this activity? How might we address those barriers in the future?

3.3. Data Analysis

Notes from the interviews were systematically recorded and taken during the interview process by Author 2. Thematic analysis (Kvale, 1996) was used to analyze the data. Data patterns that recurred in the dataset and helped answer this study's RQs — LA perceptions (RQ1) and challenges inhibiting PLA adoption (RQ2) — were named as "themes." As a means to verify interpretations in qualitative research, Author 2 identified themes related to each RQ and Author 1 verified or refined these. This process led to a further clustering of themes around specific roles and departments. It was deemed important to examine whether sample characteristics, such as the role of each interviewee in the institution, map with specific perceptions and challenges. In particular, after careful inspection of themes, commonalities and few differences were identified across different parts of the university in relation to PLA approach or adoption (see Table 1). The outputs from the interviews were first organized and discussed around different departments (Science, Business, Teaching and Learning) and roles (student engagement and support, tuition delivery, data professionals; see Results section) and then summarized and discussed as a whole (see Discussion and Conclusions section). These outcomes entailed certain actions/suggestions as to how the university could facilitate the adoption of PLA. These were identified and discussed in the form of recommendations for implementing PLA at the Open University UK.

4. Results

In the next paragraphs, themes from the interviews are discussed in relation to specific departments and roles in the university. Table 1 presents a visual representation of the main ideas by faculty and role and how these map to the eight recommendations presented in the next section.

Science faculty: In relation to RQ1, representatives from the Science faculty expressed a positive view about the potential of PLA to support student learning. The four stakeholders were confident that PLA would eventually form part of the university's official plans for retaining students. As one of the interviewees explained, "We are keen! Feedback is positive. It will become a key part of retention plans." In terms of current challenges in using PLA, they expressed the need for more insight as to how PLA could be used and when, and this could be achieved by further evaluating PLA systems used across the university. As one interviewee stated, "We need more information to know how and when to use it best" (Science interviewee 1), while another interviewee stated, "The jury is still out on the best way to use it" (Science interviewee 2).

In terms of RQ2, amongst the factors explaining the relatively slow uptake of PLA was teacher workload, which may inhibit teachers from systematically engaging with PLA systems. Furthermore, the fact that courses have varied set-ups and learning designs (see also Nguyen et al., 2017) may limit the adoption of a standardized PLA approach. One suggestion made was to consider the introduction of PLA during a key review stage in the course lifecycle (e.g., at the beginning or triggered by a midterm review). These are key points during which teaching strategies and related contact strategies are reviewed against student outcomes and therefore the introduction of PLA would be more acceptable as a strategic educational intervention evidenced through the course review.

Business faculty: The management of the Business faculty was found to strongly support the PLA initiative and its wider implementation across the university. They already had set plans to move from optional use of PLA to mandatory use for courses starting in 2018 onwards. This will allow them to gather more data about how best to use PLA. Interviewees were confident that this was the way forward: "It is born out of good research" (Business interviewee 1). The five stakeholders perceived teachers as being the key agents for contacting students at risk of failing their studies, as flagged by PLA systems (RQ1).

The limited usage and engagement with PLA by teachers (RQ2) was explained by institutional changes that affected teachers' work (i.e., changes in tuition policy and new online tuition tools), and wider institutional barriers, such as the need for more research and evaluation in order to convince teachers about the effectiveness of PLA tools. As one person explained, "The tools need to be able to sell themselves" (Business interviewee 1). In addition, interviewees identified that "Using it on a voluntary basis does not work... we need to be clear on how much easier we can make life for teachers with it" (Business interviewee 3). What is needed to achieve wider adoption is "to be part of the strategy" (Business interviewee 1) and not an optional add-on.

Table 1: Themes from Interviews with 20 Education Managers (Organized by Faculty)

Themes	RQs	Science faculty	Business Faculty	Teaching and Learning Unit	Student engagement and support	Tuition delivery	Data professionals
General perceptions	RQ1	Positive	Positive	Positive	Positive	Positive	Positive
Perceived challenges	RQ2	Lack of evaluation (Rec. 1)*; Lack of understanding as to how to use PLA (Rec. 2; Rec. 7)	Lack of evaluation (Rec. 1); Lack of understanding as to how to use PLA (Rec. 2; Rec. 7)	Lack of systematic evaluation (contradictory outcomes) (Rec. 1; Rec. 7)	Lack of evaluation (Rec. 1; Rec. 7)	Course design should define PLA use	Alignment across stakeholders (Rec. 3); Development of digital skills
Factors explaining slow uptake	RQ2	Teachers' workload (Rec. 5); Varied course designs	Institutional changes impacting teachers' work (Rec. 5); Lack of evidence about PLA effectiveness (Rec. 1)	Lack of ongoing support; Development of relevant skills	Management priorities (Rec. 4); Investment in staff	Lack of evidence (Rec. 1); Voluntary nature of participation; Lack of training; Teachers' contracts (Rec. 5)	Lack of a common vision about PLA (Rec. 6)

**Rec. stands for "recommendation"; see next section*

Teaching and Learning Unit: In terms of RQ1, interviewees from the central teaching and learning unit perceived PLA tools as highly relevant to supplementing decisions about when and who should contact students as part of a communication strategy. As explained, for them "the outcomes of using it were positive" (TLU interviewee 1). In the case of access courses, a first pilot evaluation of SPM showed increase in student numbers in groups informed by PLA data, yet the outcomes were not significant. They perceived this evidence as adequate for integrating PLA insights when making contact with students. In terms of wider adoption (RQ2), they raised the need for ongoing support when using PLA tools, development of relevant skills and resources available to support the tools. Concerns were raised around the "plethora of data and sometimes contradictory outputs" (TLU interviewee 1) and "not enough data resources and people" (TLU interviewee 2).

Student Engagement and Support: Interviewees from Academic Services supporting students were generally pleased with the early evidence of PLA impact on student retention and performance, and highly positive about their potential to support students and their learning experience: "So far the experience is very positive" (Academic Services interviewee 1). In terms of barriers to PLA adoption, they perceived these as being more relevant to immediate management priorities, as the past year has seen a significant re-organization of student support across the unit with the closure of seven regional centres and the creation of four larger student support centres. This has meant management priorities focused on short-term matters, such as allocating available resources to make contact with students at risk of failing, rather than the use of PLA per se.

One interviewee raised the issue of the need to invest in staff to undertake the work as a "barrier to success" (Academic Services interviewee 3). Limited staff availability often results in intervening with students at risk (as predicted by PLA) by emailing them once, rather than giving them a phone call, which is perceived as being more effective. Overall, some questioned the existing approaches to intervention (e.g., email or phone call) and whether these were appropriate and effective. There was also a concern that PLA is at an early stage of development and there is not enough evidence to know whether it should be used widely or not.

Tuition Delivery: Interviewees from the science and business departments expressed views about how their teaching staff had responded to early use of PLA (RQ1). Teachers from the Science faculty were found to be keen in using PLA in their practice. Yet, this does not seem to be the case across the university. While some teachers could see the value of using PLA in supporting and enhancing the learning experience, others perceived PLA as threatening the teacher's ability to understand and manage student engagement online. A distinction was made between courses where teachers have frequent contact with students and courses with less contact. Teachers suggested that in the case of the former, PLA may not add much value as they were already aware of what students were engaged with from personal contact, whereas in the latter PLA may be essential. It was also suggested that PLA should not be seen as attempting to replace teacher contact, but rather as a supplementary tool to support the teaching practice.

In terms of RQ2, the slow uptake and adoption of PLA was partially attributed to a lack of evidence showing the effectiveness of using PLA on student performance and retention. Other issues included the voluntary nature of participation, which in turn led to a lack of data to adequately demonstrate (or not) PLA impact, teachers' contracts (which do not foresee engagement with PLA), and extra time required for receiving training about PLA. It is noted that the voluntary nature of using PLA was adopted as a response to teachers' concerns about workload, yet it seems that it led to problems in relation to the appropriate evaluation of PLA and its impact.

Data Professionals: Two data professionals were included in the interviews, one from the Science faculty and one from the Strategy Office. Data professionals expressed a strongly positive perspective about the future of PLA use. They perceived PLA as being core to the vision of open and distance learning institutions or institutions "of the cloud." Yet, they raised the need for greater alignment between different stakeholders across the university in order to better support intervention strategies. They also raised issues of ownership of the PLA initiative, as this is neither owned by the data community nor the academics and student facing units: "There is a need for overarching ownership" (Strategy office interviewee 1). Ownership would ensure a common vision across separate units and more effective implementation. They also raised issues about "a general lack of digital skills" and data literacy across staff that may prevent or discourage engagement with PLA (Science interviewee 4).

5. Discussion and Conclusions

Given that several institutions have recently begun using PLA, we were keen to explore the perspectives of relevant stakeholders — in this paper, educational managers (e.g., senior management, student support officers) — about PLA adoption. Interviews conducted with 20 university stakeholders at a distance learning institution revealed a consensus in relation to adopting PLA systems to support teaching and learning at the Open University UK. In terms of RQ1, a common recognition was identified across support services, tuition representatives, and faculties that PLA has benefits and should be used especially across open, distance, or "cloud" institutions. This perception could be explained by the limited face-to-face and ongoing interaction between students and teachers in online settings, as opposed to face-to-face teaching, that makes necessary the search for other sources of information to inform teaching. In terms of how PLA should be used in the future, teaching and learning representatives pointed to PLA as a tool to inform decisions about who to contact and intervene with as part of the student support service.

In contrast, representatives from the Business faculty perceived teachers as the stakeholders best placed to act upon PLA and intervene with students at risk of failing. Yet, tuition representatives raised issues in relation to the latter; some teachers were found to be reluctant, or even threatened by the use of PLA in their practice, while others were found to be positive and recognized the value of PLA for student support. The use of PLA by teachers was not perceived as the way forward; rather a distinction was made between courses that are more suitable to adopting PLA, such as those lacking frequent interaction between teachers and students. PLA was perceived as a supplementary tool, not one replacing or changing existing teaching and learning practice. In response to RQ2, several challenges were raised as inhibiting the wider adoption of PLA across the university that could be conceived of as demonstrations of "resistance to change" (Coetsee, 1993; Piderit, 2000) at both the organizational and the individual level. These were related to management priorities, teachers, and evidence of effectiveness.

A lack of strong evidence that proves the effectiveness of PLA to support students at risk was perceived as more likely explaining the slow uptake of PLA. In part, this "lack of evidence" of effective PLA approaches might be a symptom of resistance to change; some participants indicated that the system should "sell" itself, and if it did not it would not be very useful. It is noted that strong evidence about the effectiveness of PLA on student performance and retention are now starting to emerge (Herodotou et al., under review), and strategic plans are in place to share these across the institution in order to address such concerns. In addition, there was a need for evidence as to which student support interventions (e.g., email, phone call, text) are more effective and should follow the PLA identification of students at risk. Such evidence should be used to guide and support PLA use. In terms of teachers, issues raised were related to the lack of contract provision to use PLA, heavy workload, academic resistance or reluctance to PLA, and lack of digital skills and data literacy.

Managerial priorities were also a common theme discussed across participating stakeholders as inhibiting uptake. Interviewees raised the need for a university-level PLA strategy and setting up of a common vision to guide the cohesive implementation of PLA across the institution. A top-down decision would make PLA mandatory, not optional (as it is at the

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moment), meaning that resources would need to be invested to support its implementation, satisfy the need for ongoing support when using the tools, and coordinate use between stakeholders to better support PLA interventions.

Aligning with studies that emphasize the significant role of managers in softening resistance to change (Moolenaar et al., 2010; Jippes et al., 2013), representatives across the university under study were found to "buy in" the idea of using PLA to enhance teaching and learning, a considerable step towards facilitating PLA adoption. Yet, they also raised the need for further action, in particular the need for strategic decision making at the managerial level that could lead to the wider implementation of PLA in HE. The consensus among interviewees about the benefits of PLA suggests that organizational change is more likely to be enacted at a top-down, managerial level, yet only after PLA becomes a priority and resources are dedicated to its wider implementation. For a successful PLA uptake, support is needed from both senior management and the work floor (Rienties, Boroowa et al., 2016). In terms of the latter, evidence suggest that reluctance and resistance to PLA exists at the work-floor level and across teachers. Teachers tend to rely on their own expertise or willingness to identify and contact students at risk. Introducing PLA means that teachers should modify existing practice and include external recommendations of who might be at risk. The longstanding positions of teachers at the institution and their contractual agreements that do not contain provisions for using PLA systems may more likely explain resistance to change.

Drawing from the above findings, we propose the following eight recommendations (see Figure 3) for facilitating PLA implementation at the Open University UK. These recommendations aim at recognizing and overcoming potential sources of resistance to change, as discussed by interviewees and thus facilitate adoption across the organization at both the managerial and the work-floor levels.

1. Provide evidence of PLA effectiveness for quick uptake across the organization: Provide robust evidence as to whether suggested PLA interventions work in terms of better learning outcomes, teaching practice, and supporting students at risk.
2. Provide evidence-based suggestions about effective student support interventions to be used following PLA insights: Given willingness to adopt PLA across the institution, detailed guidelines are needed about how PLA fits or modifies existing practice, including recommendations about which strategies are more effective for supporting students at risk of failing their studies.
3. Allocate resources for communication across stakeholders: Time and resources should be dedicated in order for those involved (managers, teachers) to communicate and develop a shared understanding of how, when, and why PLA should be adopted across the organization.
4. Allocate managerial time to make PLA a priority across the institution: To avoid a fragmented application of PLA, managers need to be systematically involved in the implementation by dedicating time for managing, overseeing, and guiding the implementation.
5. Consider possible teacher resistance and ways to mitigate it (ongoing support, training, involvement in the implementation, etc.): Resistance to change is well reported in the literature. Therefore, a plan to mitigate resistance and ensure meaningful adoption of PLA by teachers and other stakeholders should be implemented, including, for example, the provision of appropriate training and ongoing support to those making use of PLA as well as inclusion of representatives in all stages of implementation.
6. Set a common PLA vision to guide implementation across different units of the institution: As PLA initiatives involve interactions amongst multiple and diverse stakeholders, a shared written vision of why the implementation is taking place and what is expected from it should be devised and used as a point of reference in discussions towards effective implementation.
7. Use PLA to inform decisions about who needs support and who will act upon PLA insights: In terms of actual implementation, PLA insights should be used to inform decisions about which students need support and when (what point during the lifecycle of a course) as well as who should provide this support (teachers, student support services).
8. Use PLA as a tool to supplement — not replace — existing teaching practices: PLA can be a powerful tool for complementing the teaching practice, especially within online learning conditions where student–teacher interactions are restricted. PLA can be a great source of information about whether students are engaged online as well as whether their learning history and other characteristics may pose a risk to success in their studies.

Figure 3: Guidelines for the implementation of PLA at the Open University UK.

Overall, this paper described a qualitative approach to understanding how PLA is perceived across a single distance learning institution. Interviews with 20 educational stakeholders from different departments and roles across the university ensured that a range of different voices involved in PLA were heard and considered. A set of recommendations that can direct the effective implementation of PLA at the Open University UK were devised. These are relevant to how PLA insights should be used and how the existing institutional structures can respond to encompass change and facilitate adoption. Since evidence is drawn from a single case study, a UK distance learning institution, additional studies to examine and compare PLA implementations between HE institutions, both distance and campus-based ones, will be useful. Yet, insights from this study may transfer to other distance learning HE providers in which learning is remote and mainly asynchronous, and teachers and support teams facilitate the learning process. While this study provided suggestions about how best to support PLA implementation across a large organization for the benefit of students and teaching practice, additional case studies could provide examples of how PLA is successfully put into practice, including how resistance from teachers can be overcome or how PLA could best be used for advancing and informing learning.

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