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Learning analytics in European higher education–trends and barriers

Citation for published version:
Tsai, Y-S, Rates, D, Moreno-Marcos, PM, Muñoz-Merino, PJ, Jivet, I, Scheffel, M, Drachsler, H, Kloos, CD & Gaševi, D 2020, 'Learning analytics in European higher education–trends and barriers', *Computers & Education*, vol. 155, 103933. https://doi.org/10.1016/j.compedu.2020.103933

Digital Object Identifier (DOI):
10.1016/j.compedu.2020.103933

Link:
Link to publication record in Edinburgh Research Explorer

Document Version:
Peer reviewed version

Published In:
Computers & Education

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Highlights

Learning Analytics in European Higher Education–Trends and Barriers

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- Research highlights item 3

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Learning Analytics in European Higher Education–Trends and Barriers?

ARTICLE INFO

Keywords:
Learning analytics
Cultural and social implications
Data science applications in education
Cross-cultural projects
Post-secondary education

ABSTRACT

Learning analytics (LA) as a research field has grown rapidly over the last decade. However, adoption of LA is mostly found to be small in scale and isolated at the instructor level. This paper presents an exploratory study on institutional approaches to LA in European higher education and discusses prominent challenges that impede LA from reaching its potential. Based on a series of consultations with senior managers from 83 different higher education institutions in 24 European countries, we observe that LA is primarily perceived as a tool to enhance teaching and institutional management. As a result, teaching and support staff are found to be the main users of LA and the target audience of training support. In contrast, there is little evidence of active engagement with students or using LA to develop self-regulated learning skills. We highlight the importance of grounding LA in learning sciences and including students as a key stakeholder in the design and implementation of LA. This paper contributes to our understanding of the development of LA in European higher education and highlights areas to address in both practice and research.

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1. Introduction

Learning analytics (LA) as a field emerged a decade ago in response to the digitalisation of education and the maturity of data mining technology (Ferguson, 2012). Under the growing pressure of financial sustainability and competition with the global market, the higher education (HE) sector is driven to demonstrate evidence of quality educational offerings. As a result, LA has risen as a means to measure learning and answer difficult questions pertaining to the overall performance of an institution in the HE sector (Viberg, Hatakka, Bälter, & Mavroudi, 2018). Despite the growing interest in using data analytics to inform educational decisions and personalise support for students, the sector has struggled to establish the value and impact of LA on the improvement of learning (Ferguson & Clow, 2017; Viberg et al., 2018). In the recent NMC Horizon Report, adaptive learning as a key objective of LA has fallen out of the list of key development areas in HE after being featured for four consecutive years (Alexander et al., 2019). In light of the trends of educational technology development and deployment, the report argues that adaptive learning technology has not been able to scale up to its potential due to various challenges in institutional adoption (Alexander et al., 2019). Our paper responds to this observation by outlining the trends in and barriers to LA adoption in the European HE sector. Our intention is to provide insights into shaping the practice and research in the field as it moves into a new decade. This paper attempts to answer the research question:

What is the state of the art in terms of learning analytics adoption in European higher education?

Drawing on survey and interview data collected in a large-scale study, we present detailed analyses of the observed phenomena, and reflect on the implications of how LA has been conceptualised and applied. In particular, we identify gaps in the roles of teachers and students in the adoption process. The study presented in this paper is by far the largest in terms of the geographical coverage, as opposed to similar studies of its kind in the same region (Ferguson et al., 2016; Nouri et al., 2019). The paper contributes to our understanding of the complex issues that impede LA from scaling, provides concrete cases illustrating the approaches taken by higher education institutions (HEIs) to move technological innovations into operation, and challenges researchers and practitioners to reflect on where we are with LA and areas to improve in order to scale the potential of LA.

? This document is the results of the research project funded by

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2. Literature review

2.1. Learning analytics in higher education

Learning Analytics (LA) is commonly defined as “the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs”(Long, Siemens, Conole, & Gašević, 2011). Essentially, LA makes use of the data footprints produced by stu-dents when interacting with digital technologies in the learning process for the purpose of leveraging human decisions such as designing educational interventions (Siemens & Baker, 2012). Commonly used methods to distil information and visualise data include clustering analysis, network analysis, text mining, process and sequencing mining (Daw-son, Joksimovic, Poquet, & Siemens, 2019; Leitner, Khalil, & Ebner, 2017; Matcha, Gašević, Uzir, Jovanović, & Pardo, 2019; Viberg et al., 2018), although scholars have also argued the need to scale up qualitative research in the field (Gašević, Dawson, & Siemens, 2015) and the importance of grounding the designs of LA models and studies in learning theories (Gašević, Kovanović, & Joksimović, 2017). Overall, the field of LA aims to “harness unprecedented amounts of data collected by the extensive use of technology in education”(Gašević et al., 2017)(p. 63). Importantly, it promises to provide insights helpful for enhancing teaching practice, learning decisions, and educational management (Siemens & Baker, 2012).

Under the constant pressure of quality evaluation and financial stability, the HE sector has turned its attention to LA for solutions to issues around student progression and retention, learning experience and student satisfaction, teaching quality and innovations, and institutional performance and ranking. Some of the reported motivations to adopt LA include reducing student dropout and increasing academic success (Leitner et al., 2017; Sclater, Peasgood, & Mul-lan, 2016; Viberg et al., 2018; Wong, 2017), understanding learning behaviours, processes, and strategies (Avella, Kebritchi, Nunn, & Kanai, 2016; Leitner et al., 2017; Matcha et al., 2019), informing curriculum design and learn-ing support (Avella et al., 2016; Leitner et al., 2017), personalising learning systems and resources such as course recommendations (Avella et al., 2016; Brown, DeMonbrun, & Teasley, 2018), and developing self-regulated learning skills with data-based, timely feedback (Pardo, Jovanovic, Dawson, Gašević, & Mirriahi, 2019). Although interest in adoption of LA in pre-tertiary education is rising, current efforts are found to accentuate in the HE sector with a study reporting 60% of LA publications being based in the HE context (Dawson et al., 2019).

In the global landscape, the USA has been identified as the leading research hub based on publication outputs fol-lowed by Spain, the United Kingdom, Australia, Germany, Canada, India, the Netherlands, Japan, and China (Waheed, Hassan, Aljohani, & Wasif, 2018). However, empirical studies on the deployment of LA in HE are notably small in scale, although there have been a paucity of nation-wide investigations (Arroway, Morgan, O'Keefe, & Yanosky, 2016; Colvin et al., 2016; Mahroeian, Daniel, & Butson, 2017; Mahroeian et al., 2017; Newland, Martin, & Ringan, 2015; Sclater, 2014). In the USA, it is noted that more emphasis has been placed on using LA to monitor or measure student progress than to predict success or prescribe interventions (Arroway et al., 2016). In Australia, two types of institu-tional approaches to LA have been identified: using LA as a tool for measurement or efficiency gains versus using LA as a means to reflect on factors contributing to learning outcomes (Colvin et al., 2016). In New Zealand, a study noted that a majority of senior managers in HE see LA either in the forms of structures (e.g., statistics, metrics, and graphs) or on functional grounds (e.g., a tool or process to answer difficult questions and inform decision-making), with only a small number of participants conceptualising LA in both structural and functional forms (Mahroeian et al., 2017). In the UK, only a handful of institutions have reported the use of LA (Newland et al., 2015), and the nascent phase of adoption makes it difficult to evaluate impact (Sclater et al., 2016). Overall, the global landscape of LA adoption is embryonic, a phenomenon also observed in a systematic review of the current state of LA in HE (Viberg et al., 2018).

2.2. Challenges with Learning Analytics

Despite the optimistic prediction of LA reaching sector-wide adoption by 2017 (Johnson et al., 2016), cases of large and systematic adoption at the institutional level are scarce (Viberg et al., 2018). Empirical evidence has proven the deployment of LA to be challenging in HE where resource demands coupled with social complexities have impeded LA from reaching its full potential (Ifenthaler & Yau, 2019; Tsai, Poquet, Dawson, Pardo, & Gaševic, 2019).

Challenge 1: Stakeholder engagement and buy-in. Unequal engagement with key stakeholders of LA and insti-tutional resistance to change have been reported repetitively as barriers to cultivate shared visions and the ownership of LA (Macfadyen, Dawson, Pardo, & Gaševic, 2014; Tsai & Gaševic, 2017). As the cognitive understanding of what LA can do and the emotional attitudes towards the experience of using LA both contribute to intentional attitudes re-garding adoption (Herodotou, Rienties, Boroowa, Zdrahal, & Hlosta, 2019), scholars have campaigned for a co-design

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process for the development of tools (Shibani, Knight, & Shum, 2019), strategy (Dollinger & Lodge, 2018), and policy (Leitner, Ebner, & Ebner, 2019).

Challenge 2: Weak pedagogical grounding. Related to the problem of unequal engagement with key stakeholders are the insufficient considerations of pedagogical practice and educational theories to meet the needs of both teachers and learners (Gašević, Tsai, Dawson, & Pardo, 2019). For example, reviews of LA dashboards have revealed issues in the design and evaluation including failing to ground in self-regulated learning theories (Matcha, Uzir, Gasevic, & Pardo, in press), and prioritising acceptance, usefulness and ease-of-use (based on the technology acceptance model (Davis, 1989)) over the learner's cognitive and emotional competence (Jivet, Scheffel, Specht, & Drachsler, 2018). To ensure that LA enhances learning, it is crucial to base design and implementation on learning theories, especially when seeking to identify suitable data sources (Manderveld, 2015) and indicators of learning progression (Pardo et al., 2019; Schmitz, Van Limbeek, Greller, Sloep, & Drachsler, 2017).

Challenge 3: Resource demand. The deployment of LA requires technological, human, and financial resources. Although the investment in LA may reduce costs in the long run (El Alfy, Marx Gómez, & Dani, 2019), strategic invest-ment is required in order to address issues such as technical challenges in system-integration (Arroway et al., 2016), data interoperability, and model generalisation (Moreno-Marcos, Alario-Hoyos, Muñoz-Merino, & Delgado Kloos, 2019). Importantly, the investment includes acquiring expertise relevant to LA and making time for staff (e.g., chang-ing the work model). This challenge could be particularly pronounced in the tension between an institution's need to innovate and its existing capacity to accommodate competing priorities (Tsai et al., 2019).

Challenge 4: Ethics and privacy. The scope, volume and speed of data collection for LA have raised concerns about intruding the learner's privacy and various ethical implications. For example, Pardo and Siemens (2014) point out the tension between optimising what data can do and ensuring responsible use of data; Rubel and Jones (2016); Tsai, Whitelock-Wainwright, and Gaševic (2020) question the extent to which student consent is fully informed in the presence of the asymmetrical power relationship between students and the provider of educational services; and Tsai, Perrotta, and Gašević (in press) argue the inherent problem of diminishing the learner's autonomy through the manner in which data is collected and used to provide educational interventions. While national and international measures, such as the European General Data Protection Regulation (GDPR) (The European Union, 2016), have set out general guidelines to protect data subjects, the lack of examples in practice has left much space for interpretations of legal frameworks in different local contexts.

2.3. Learning Analytics adoption approaches

Over the years, several frameworks, models and approaches have been proposed to assist LA adoption at an in-stitutional or instructor level. Most of these were motivated by the aforementioned challenges (Table 1). An early framework proposed by Greller and Drachsler (2012) considers six dimensions of a LA cycle: (1) stakeholders, (2) internal limitations (required competences), (3) external limitations (conventions, norms and time scale), (4) instru-ments, (5) data, and (6) objectives. The framework is proposed as a checklist to set up LA and mitigate challenges. Also focusing on setting up LA, the Learning Analytics Readiness Instrument (LARI) (Arnold, Lonn, & Pistilli, 2014; Oster, Lonn, Pistilli, & Brown, 2016) evaluates the readiness of institutions to implement LA. It contains five main components: (1) ability, (2) data, (3) culture and process, (4) governance and infrastructure, and (5) overall readiness perception. LARI serves to assist HEIs to identify their strengths and weaknesses when it comes to implementing LA. Also aiming to scale up the readiness of HEIs, the LALA framework, developed in Latin America, contains four dimensions: (1) institutional, (2) technological, (3) ethical, and (4) community (Sanagustín et al., 2019). This frame-work provides detailed steps to identify the needs of different stakeholders, design, implement, and evaluate LA tools according to the needs, consider ethical implications in policy development, and build up a community to develop LA practice and research.

Among all the prominent challenges of LA, ethics and privacy aspects have attracted much attention. Slade and Prinsloo (2013) proposed six principles to ensure ethical use of LA: (1) LA as moral practice, (2) students as agents, (3) student identity and performance are temporal dynamic constructs, (4) student success is a complex and multidi-mensional phenomenon, (5) transparency, and (6) HE cannot afford to not use data. The authors stress that student perception of LA depends on whether they understand the purpose of and the motivation behind it and that there is a danger of categorising students on historical data. Proposed before the European General Data Protection Regulations 2016/679 (GDPR) (The European Union, 2016) came into effect, these principles are still relevant to the HEI contexts

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in Europe and beyond. Also focusing on the role of students in a LA process, Rubel and Jones (2016) stress five key questions to ask when discussing privacy and ethics in LA: (1) privacy and information flows with respect to whom, (2) privacy about what, (3) accounting the benefits and burdens of data collection, (4) stakeholder awareness and control, and (5) whether such data collection conflicts with the purpose of HE. Similarly, the DELICATE list by Drachsler and Greller (2016) considers eight areas: (1) determination (purpose), (2) explain (transparency), (3) legitimate (le-gal and meaningful use/collection of data), (4) involve (stakeholders), (5) consent (contracts with data subjects), (6) anonymise, (7) technical (procedures of data protection), and (8) external partnership.

Another approach to LA is taken from the perspective of policy development. Macfadyen et al. (2014) argue that successful institutional adoption requires comprehensive policies that recognise educational institutions as complex adaptive systems. They proposed an adapted version of the Rapid Outcome Mapping Approach (ROMA) (Young & Mendizabel, 2009) to be used in the LA context by following the following steps: (1) defining a clear set of overarching policy objectives; (2) mapping the context; (3) identifying key stakeholders; (4) identifying LA purposes; (5) develop-ing a strategy; (6) analyzing capacity and developing human resources; and (7) developing an evaluation system. Also building on the ROMA framework, the SHEILA Framework (Tsai et al., 2018) contains a repository of key actions that may be taken in each of the step described above, key challenges to address, and key questions to answer when developing a comprehensive policy to address the identified actions and challenges.

Besides policy, institutional management and leadership are considered key to systematic and sustainable adoption of LA. Based on empirical data collected in 32 Australian HEIs, Colvin et al. (2016) propose a dynamic model that highlights the strategic capabilities (leadership, strategy, institutional readiness) and operational capabilities (capacity and infrastructure) as primary forces that steer the adoption of LA in HE. Based on the same set of data, Dawson et al. (2018) used complexity leadership theory (Lichtenstein et al., 2006) as a lens to analyse the presence of leadership in LA adoption. They uncovered two models of leadership, a top-down and a bottom-up approach, each with its own benefits and pitfalls. Applying the same theory in the UK context, Tsai et al. (2019) argue that prominent challenges with LA adoption reside in the tension between innovation and operation. In light of this, they emphasise the importance of enabling leadership in nurturing an adaptive space for LA related innovations. Considering all the approaches discussed above, Gašević et al. (2019) stress three key elements of systemic adoption: 1) data and its limitations, 2) models used for processing and analysing data, and 3) institutional transformation (policy& strategy, leadership, privacy& ethics, user-centred, and data-informed).

As discussed earlier, buy-in from key stakeholders have been identified as an important dimension of LA adoption and a prominent challenge to address, scholars have proposed models specifically meant to engage different stake-holders in the adoption process. West, Heath, and Huijser (2016) stress the role of dialogue and propose a frame-work to systematise and contextualise conversation about LA implementation for student retention. Similarly, Prieto, Rodríguez-Triana, Martínez-Maldonado, Dimitriadis, and Gašević (2019) emphasise the need to reach a common understanding among stakeholders including teachers, developers and researchers. They propose OrLA – a communi-cation tool that guides and supports decision-making about the design and implementation of LA. In response to the challenge of academic resistance, Herodotou, Rienties, Verdin, and Boroowa (2019) makes a number of recommen-dations including providing evidence, promoting cross-stakeholder communication, allocating managerial time, and complementing teaching practice.

Based on the models and approaches discussed above, we can see that stakeholder involvement is an area most frequently highlighted. This is followed by ethics and privacy issues, and the two challenges are often intersected (Table 1). However, it is also clear that the challenge of weak pedagogical grounding, as identified in the previous section (Section 2.2), has received comparatively little attention. To what extent do the existing frameworks reflect institutional priorities in their approaches to LA? We return to this point at the end of the article.

3. Methodology

This study adopts mixed methods using a survey and interviews. The former was primarily distributed through the European University Association (EUA) to 249 HEIs (from 38 countries in Europe) that had previously responded to an e-learning survey conducted by EUA regarding institutional experiences in e-learning (Gaebel, Kupriyanova, Morais, & Colucci, 2014). We further promoted the survey via newsletters of European-wide professional networks such as European University Information Systems Organization (EUNIS), European Association of Distance Teach-ing Universities (EADTU), and through some professional networks in Spain, the UK, and the Netherlands where the authors were based. The interviews adopted an opportunistic sampling method (Tracy, 2013) to take advantage of the

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Frameworks / Models	Ch1	Ch2	Ch3	Ch4
Greller and Drachsler (2012)	x	x	x	x
Slade and Prinsloo (2013)	x			x
Arnold et al. (2014); Oster et al. (2016)	x		x	x
Macfadyen et al. (2014)	x		x	x
Colvin et al. (2016)	x		x	x
Drachsler and Greller (2016)	x			x
Rubel and Jones (2016)	x			x
West et al. (2016)	x			
Dawson et al. (2018)	x		x	x
Tsai et al. (2018)	x		x	x
Gašević et al. (2019)	x	x	x	x
Herodotou, Rienties, Boroowa, et al. (2019)	x			
Prieto et al. (2019)	x			
Tsai et al. (2019)	x		x	x
Sanagustín et al. (2019)	x		x	x

Table 1
LA adoption models and the addressed challenges (Ch1 – stakeholder engagement and buy-in, Ch2 – weak pedagogical grounding, Ch3 – resource demand, and Ch4 – ethics and privacy) (see Section 2.2)

researchers' existing network and influence. The in-depth conversation allowed us to gain deep insights into the current adoption of LA in European HE. Both the survey and interviews were conducted online, involving senior managers from 83 different institutions in 24 different European countries (Table 2). The comparatively high number of partic-ipants from Spain and the United Kingdom coincides with the high levels of research outputs in these two countries in the European region (Waheed et al., 2018), as discussed in Section 2.1. According to Waheed et al. (2018), among the 15 institutions that had the highest publication outputs on LA by 2017, seven were European institutions. Among these, two institutions (from Finland and Spain) participated in our survey, while another two, different, institutions (from the UK and Spain) participated in our interview. We describe the data collection and analysis processes below.

3.1. Survey

The survey[1] consists of 28 questions that explore the adoption status and maturity of LA among European HEIs. The adoption status section includes questions investigating existing LA initiatives, institutional infrastructures for LA, adopted strategies and policies for LA, considerations of legal and ethical issues, and existing evaluation frameworks. The LA maturity section asks participants to self-evaluate the engagement of key stakeholders (i.e., teaching staff, students, and managers), success of LA, institutional culture, data and research capabilities, legal and ethical aware-ness, and existing training. The survey was validated by two experts and updated subsequently to improve clarity (e.g., definition of LA, question wording, order, and examples) and reduce length by removing similar questions. All the changes were made in agreement after discussion involving all the reviewers and designers of the survey. Afterwards, the survey was distributed widely among European HEIs targeting senior managers. Forty-five institutions from 23 countries responded, of which 15 have implemented LA, 15 were in preparation to implement LA, and 15 were in-terested in implementing LA. The survey was open from September 2016 to February 2017. A descriptive statistical analysis was carried out on the data.

3.2. Interviews

We conducted 54 interviews between August 2016 and February 2017, and 46 HEIs across 14 countries took part in this activity[2]. Among these institutions, eight also participated in the institutional survey. The participants in the interviews ranged from Vice Presidents/ Deans of Learning and Teaching to Heads of IT, Directors of E-learning Centres, and positions established specially for LA research and development. The average length of the interviews was 44 minutes. The number of participants in each interview ranged from one to three, and some participants from the same institution attended the interviews separately. This resulted in a total number of 68 participants. Ten interview

1The questionnaire is available at http://bit.ly/institutional_survey

2The demographic information of the sample is available at http://bit.ly/interview_meta

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Countries	Survey	Interviews
Austria	2	1
Bulgaria	1	0
Croatia	0	1
Cyprus	1	0
Czech Republic	1	1
Denmark	2	0
Estonia	3	0
Finland	3	0
France	0	1
Germany	3	1
Hungary	1	0
Ireland	2	2
Italy	1	2
Lithuania	1	0
Netherlands	2	1
Norway	1	1
Portugal	1	2
Romania	2	1
Serbia	1	0
Slovakia	2	0
Spain	5	10
Switzerland	1	1
Turkey	1	0
United Kingdom	5	21
N/A	3	0
Total	45	46

Table 2
Countries of institutions involved in the survey and interviews (8 institutions participated in both activities)

questions were developed to investigate (1) institutional plans for LA, (2) motivations for LA, (3) adopted strategy, (4) strategy development processes, (5) readiness preparations, (6) success and evaluation, (7) success enablers, (8) challenges, (9) ethical and privacy considerations, and (10) the interviewee's views of essential elements in a LA policy[3]. All interviews were video-recorded with consent received from the participants in advance.

The data was analysed using a thematic analysis assisted by the NVivo software [4]. A coding scheme consisting of two types of variables (implementation and readiness) and ninety-nine codes was developed based on relevant literature (Colvin et al., 2016; Tsai & Gaševic, 2017) to assist us with interrogating the data in a systematic way[5]. Four researchers in total participated in the coding process. The process of ensuring the coding consistency was as follows. The leading researcher proposed an initial coding scheme and explained the meaning and usage of each code to the other three researchers. All the researchers then practised coding the same interview transcript independently and compared the results afterwards to resolve disagreement or revise the coding scheme. This process was repeated twice (with two different interviews in total) until the agreement on each code was above 85% based on the coding comparison query.

In the next section, we draw on findings from both survey and interview data to answer the research question – What is the state of the art in terms of learning analytics adoption in European higher education? Specifically, we look at the current trends (Section 4.1) and barriers (Section 4.2). In terms of trends, we examine adoption experience (Section 4.1.1), motivations and approaches (Section 4.1.2), and strategy (Section 4.1.3). The interview quotes are labelled with the letter U (denoting university) followed by a case number and the country location.

3The interview questions are available at http://bit.ly/interviews_questions

4NVivo allows better organisation, retrieval, and comparison of the data that researchers have manually coded.

5The coding scheme is available at http://bit.ly/interview_coding

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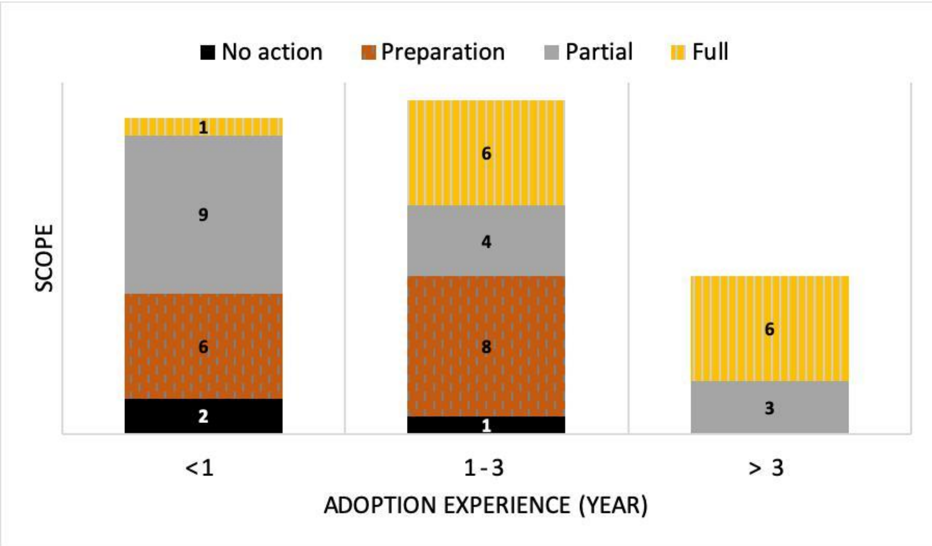

Figure 1: LA adoption scope and years (interview, n=46)

4. Findings

4.1. Trends of adoption in European higher education

4.1.1. Adoption experience

The majority of the institutions had less than three years of experience adopting LA. As Figure 1 and Figure 2 show, only 9 out of 46 institutions that participated in the interviews and 7 out of 45 institutions that responded to the survey had more than three years of experience. In terms of the scope, we labelled institutions by 'full'(institution-wide implementation), 'partial' (implementation at piloting scales or in parts of the institution), 'preparation' (in preparation to implement LA), and 'no action' (no action was taken in preparation for the institutional adoption of LA)6. The data shows that institutions that participated in the interviews have reached a larger scope of adoption compared to survey respondents: 29 out of 46 interviewed institutions had implemented LA on a partial or institution-wide scale, whereas only a third of the survey respondents had reached these scales (15 out of 45 institutions). One possible explanation of the observed discrepancy is that the opportunistic sampling method (Tracy, 2013) of the interviews filtered participants by adoption experience to some degree (i.e., institutions that had adopted LA were more likely to know other institutions that had similar experience and introduced them to the researchers). Nevertheless, we can see a natural progression in the scope of adoption when the experience of LA increases. For example, Figure 1 shows that the proportion of institutions implementing LA on an institution-wide scale increased from 1:17 among the least experienced institutions (< 1 year) to 6:3 among the most experienced institutions (> 3 years), and Figure 2 shows that only 2 of the most experienced institutions (> 3 years) among all the survey respondents have reached institution-wide adoption. The only interview case that has reached institution-wide adoption of LA within one year is worth further investigations. We return to this case (U42, UK) in Section 5

4.1.2. Motivations and approaches

Motivations. From the perspectives of managers, the drivers to adopt LA tend to be associated with institutional key performance indicators, as reflected by the four top motivations in Table 3. However, the fifth most frequently chosen motivation on the list also reveals that the value of LA for individual institutions was yet to be determined.

From our conversations with interview participants, we found that when LA was adopted to improve institutional performance or management, there tended to be a pre-identified problem, such as student retention, satisfaction, enrol-ment, or resource management, and LA was used to investigate these problem areas and to obtain insights that might inform further actions.

6The full coding scheme is available at http://bit.ly/interview_coding

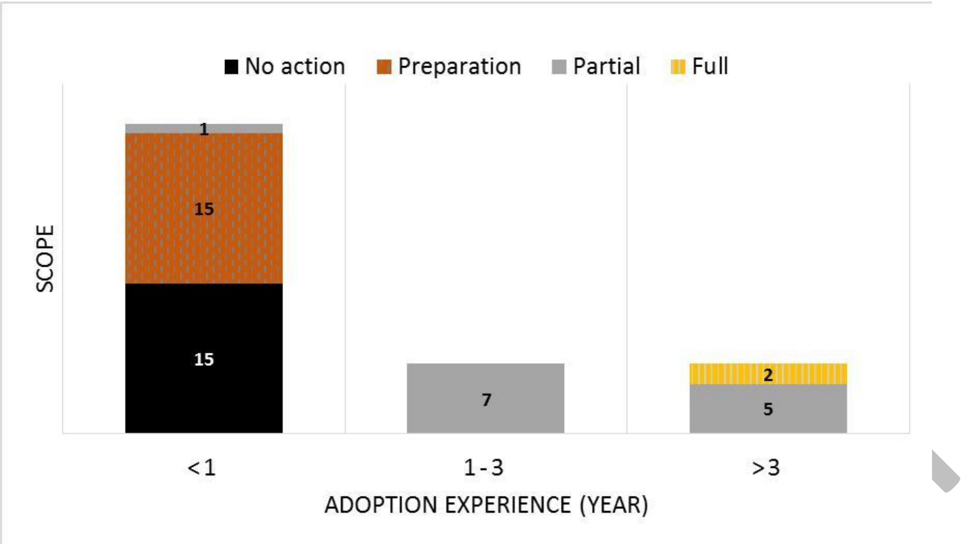

Figure 2: LA adoption scope and years (survey, n=45)

Options	Counts
To improve student learning performance	40
To improve teaching excellence	33
To improve student satisfaction	32
To improve student retention	25
To explore what learning analytics can do for our institution/ staff/ students.	25
To provide personalised learning support	18
To increase learning motivations	17
To inform curriculum	16
To encourage self-regulated learning	14
To improve student-teacher communication.	12
To improve student recruitment	11
Other	1

Table 3
Motivations to adopt LA (Survey, n=45, multiple-choice)

By integrating multiple data resources into this new BI (business intelligence) software, you can analyze [data] with some tools, diagrams and so on: what are the causes for student retention or dropout, and that is a primary focus–spotlight on this matter at the moment. – U05 (Germany)

In contrast, when the enhancement of teaching and learning support was highlighted as the motivation for adopting LA, the interview participants expressed a particular interest in going beyond measuring learning to understanding how students learn or engage with learning resources so as to provide interventions that meet the needs of learners:

There's kind of that pedagogical side in terms of well can we actually see any patterns and trends, and can we unpack that, and can we hit support people to develop more engaging learning, engaging and effective learning and teaching experiences. – U35 (UK)

Longer term people are really thinking about learning analytics as a way to try and personalise educa-tion and enhance education, and actually make our education more inclusive both by understanding how different students engage with different bits of educational processes, but also about developing curricula to make them more flexible and inclusive as a standard. – U38 (UK)

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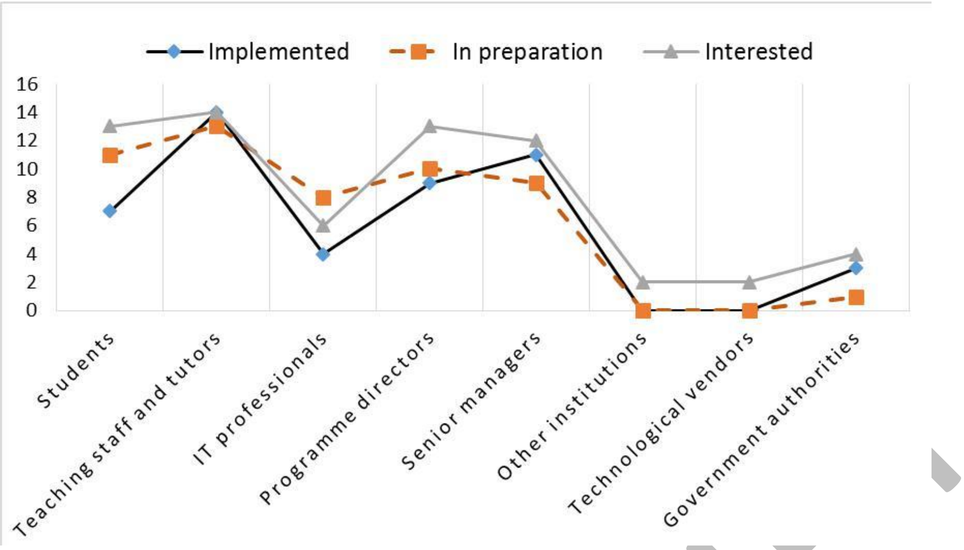

Figure 3: Users of LA (survey, n=45, multiple-choice). Among the 45 respondents, 15 had implemented LA, 15 were preparing to implement LA, and 15 were interested in implementing LA.

Primary users. While giving data back to learners is one of the key principles to support self-regulated learning using LA (Matcha et al., in press), our data shows that teaching staff and support staff (e.g., tutors and advisers) were the primary users in many cases. As Figure 3 shows[7] , when asked about with which stakeholders the institution was sharing or would share the results of LA, "teaching staff and tutors" consistently received the highest votes across three groups of respondents: those who had implemented LA, those who were preparing to implement LA, and those who were interested in adopting LA. Although "students" received the second highest number of votes among the *preparation* group and the *interested* group, it was identified as the fifth most frequent users of LA among the group of respondents who had already implemented LA. This drop alludes to the priority of user groups when implementing LA. Notably, the survey data also highlight sharing data with programme directors and senior managers.

Similarly, among the interviewed institutions, teaching and support staff were indicated as the main users by most institutions (n=36), followed by students (n=23) and senior managers (n=11)[8]. This is also reflected by an emphasis on training for teachers over training for other stakeholders. The phenomenon could perhaps be attributed to a prevailing perception that learning problems need to be addressed by making changes to teaching, and LA provides a technological solution to teaching. For example, one participant indicated:

> *They [students] are not aware of what is going on, so it [training] is for the teachers* – U12 (Portugal)

Interestingly, while the participants generally agreed that technological solutions would not necessarily empower people unless they have been trained to act critically on the data, there was optimism regarding the ability of students to make use of data compared to teaching staff:

> *For staff yes, for students no, because the idea with us is that students will have a dashboard, will have an App on their phones, and I haven't found a single App the students been training [sic] on.* – U45 (UK)

> *I think for students there will be no need [for training] because they will do it automatically, but for teachers, maybe. We would like to combine it with our effort into support for teachers to develop their teacher skills, you know, pedagogical skills. So I think there will be no need for students to educate in this, but teachers, maybe.* – U03 (Czech Republic)

In fact, none of the most experienced institutions have offered training for students.

7Some of the options are in shortened forms here. "IT professionals" was originally "IT professionals within the institution", "Programme directors" was "Curriculum and programme directors", and "Senior managers" was "Managers at department, school and institution levels" in the survey.

8In some institutions, more than one group of stakeholders were indicated as main users.

Options	Counts
VLE/ LMS (Virtual Learning Environment/ Learning Management System)	37
Assessment scores	34
Student Information Systems	32
Student surveys (e.g. course evaluation and university experience)	32
Library systems	17
Attendance monitoring systems	14
Timetabling systems	10
ePortfolios	8
Lecture capture/media streaming systems	8
Other	8
Swipe cards used for access to buildings	7
National databases	7
Social media	3

Table 4
Sources of data for LA (Survey, n=45, multiple-choice)

Options	Counts
Elements within existing institutional VLE/ LMS (Virtual Learning Environment/ Learning Management System)	33
Elements within existing institutional data management system	26
In-house developed tools/ software	24
Open source tools/software	20
Tools/ software offered by external partners	16
Tools/ software purchased from technological vendors	12
Other	3

Table 5
LA tools and software (Survey, n=45, multiple-choice)

Data and software tools. In terms of data sources, VLE/LMS (virtual learning environment/ learning management system), assessment scores, Student Information Systems, and student surveys were most frequently chosen for LA by survey respondents (Table 4). Additional sources of data indicated by the respondents include MOOC (Massive Open Online course) data, benchmark data from other HEIs, students' personal study plans, data collected by Career Services, and live voting data in the classroom.

In terms of preferred or commonly used tools and software, existing components in learning management systems were chosen most frequently by respondents (Table 5).

4.1.3. Strategy

Strategy. In terms of adopted strategy, among the 15 survey respondents that indicated existing implementation of LA in their institutions, 7 did not have a clear strategy to work towards the goal of LA; 6 had developed a strategy specifically for LA or had adopted a strategy originally developed for (an)other project(s); and two respondents indicated "Other". One of these two respondents indicated "We talk but there is no base strategy or framework", and the other specified that LA was used to support the university's wider strategy: "Mostly we use learning analytics as data to assess achievement of strategic goals. Some of KPIs base on learning analytics [*sic*]".

Several interview participants indicated that a detailed strategy for LA was yet to be developed based on the results of pilots (n=26). A participant indicated:

> *One thing that we intend to do is to document all our progresses and share those documents at institutional level, so there is a monitoring process that could eventually be used to define a strategy about a global policy for the university.* – U15 (Spain)

However, a great number of interview participants (n=32) pointed out that the adoption of LA was to support the wider university strategy, such as learning and teaching strategy, digital strategy, and equity, diversity and inclusion

Option	Involvement	Lead
Learning and Teaching Support Unit	36	26
Information Technology Services	34	12
Teaching staff	31	7
Heads of departments/ schools/ colleges	27	7
Head of the institution	26	12
Students	19	1
Personal tutors	10	0
External partners (e.g. service providers and research organisations)	10	2
Other	5	9

Table 6
Stakeholders that are involved in implementing or leading LA adoption, sorted by 'involvement' (Survey, n=45, multiple-choice)

strategy. For example, a respondent described their university's strategic structure as a 'Russian doll':

> *We are just relaunching our education strategy. Russian dolls, we have got a big institutional strategy and then the education strategy within that. And then within the education strategy we have got a focus on flexible and inclusive learning, and I think analytics will fall within that longer term.* – U38 (UK)

Although few institutions were able to provide detailed information about the evaluation process of LA, 7 interview participants explicitly indicated that their evaluation framework was informed by the key performance indicators of the wider university projects that LA supported. However, one participant also pointed out the likelihood of losing sight of the core principle that LA should enhance learning if LA is simply treated as a data management tool:

> *If you are happy with the concept that learner analytics is a subset of managing University data, then I am happy that strategically it was always there. I think what the University did not understand and had not got the buy-in to do was to actually go down the route of looking at how meaningful data could be for our learners.* – U45 (UK)

Stakeholder involvement When it comes to the involvement of stakeholders, the survey identified that the learning and teaching department in the university tends to be the most highly involved stakeholder group (n=36) and the leading force of institutional LA projects (n=26), followed by Information Technology Services. In terms of primary stakeholders, the involvement of teaching staff (n=31) and personal tutors (n=10) together is overwhelmingly higher than students (n=19), as also reflected in the result of another survey item about the main users of LA (see Figure 3).

One interview participant described this phenomenon as a potential problem:

> *Another problem is that students are not involved at all in this discussion. That's an important bottom-up stakeholder group which is not really part of this world yet.* – U10 (Netherlands)

The unbalanced involvement of teachers and students is also reflected in the much more frequent mentioning of teaching staff than students among interview participants when it came to the topic of challenges around buy-in and capability (Section 4.2).

Success. When asked about the success to date in their implementation of LA, the interview participants in general had reservations due to the early phase of adoption. Nevertheless, several institutions indicated that 'gaining expe-rience' was a positive outcome as it allows institutions to "take things potentially to the next level" (U39, UK). For example, another respondent illustrated this point further:

> *We are learning as we go, we are learning as our lecturers demand new functionalities, we are learning how students use our systems and how they perceive our activities and so on and so forth, so we gradually develop our infrastructures and expertise from the ground up.* – U25 (Switzerland)

Another respondent also indicated that gaining experience with LA helped improve the institutional culture:

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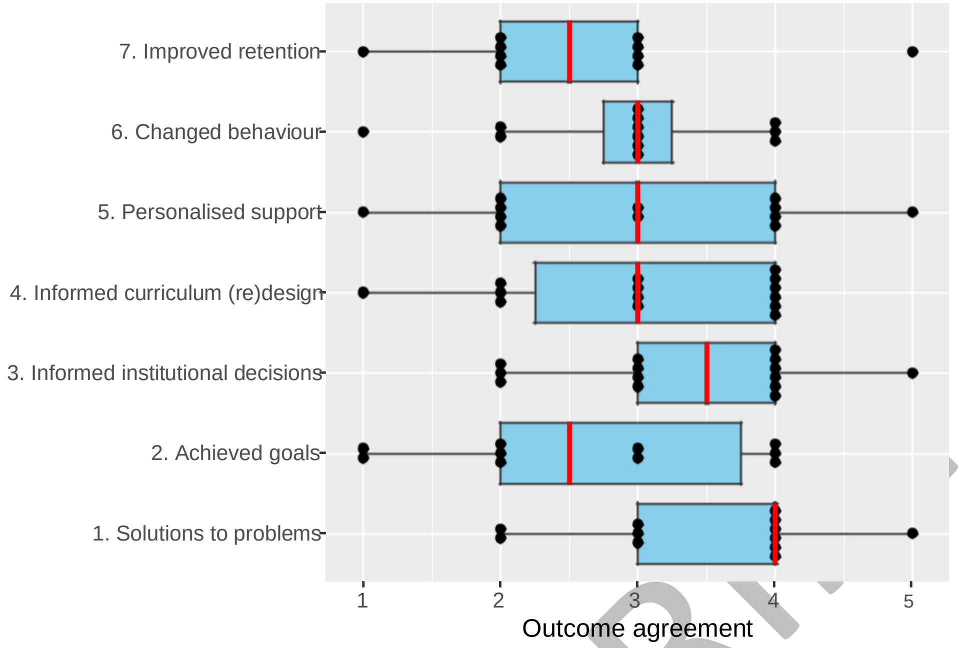

Figure 4: Implementation outcome. Medians are denoted by the red solid lines, boxes represent interquartile ranges (IQR), whiskers are 1.5 IQR, and data points are marked with grey dots. Answers to N/A are not counted. Full descriptions of items are as follows: 1. Learning analytics technology provides effective solutions to our problems, 2. We have achieved the goals that we set for learning analytics, 3. We have made some institutional decisions based on the results of learning analytics, 4. We have designed/ re-designed curricula based on the results of learning analytics, 5. Our students have received more personalised support from teaching staff/ tutors, 6. Our students have shown positive behaviour changes as a result of leaning analytics, and 7. Our student retention has improved.

> *The success of it [LA], I think, is that it is showing the possibilities and I think opened up other people's imaginations to what could be possible if we had even more or different data.* – U43 (UK)

We followed up with the participants who were able to comment on the achievements of LA adoption to tell us what might have contributed to their success. The success enablers mentioned by the participants are summarised as follows:

1. LA adoption is driven by needs, i.e., LA is adopted to tackle a pre-identified issue (e.g., retention).
2. Senior leadership drives strategic adoption.
3. Required resources are obtained, including funding, technological infrastructure, and LA expertise.
4. Cross-stakeholder conversations bring together a wide range of expertise and experience.
5. The accessibility, ease of use, and usefulness of LA attract teaching staff.

A survey question that investigated the outcome of LA implementation reveals similar results (Figure 4). A total of 15 respondents who indicated that LA was already implemented in their institutions were asked to assess the outcome using a 5-Likert scale (1 being 'strongly disagree' and 5 being 'strongly agree'). The results show that the participants were leaning towards agreement in terms of using LA as solutions to existing problems (Item 1) and using LA to inform institutional decisions (Item 3). The views towards the rest of the items appeared to be polarised, and slightly more negative about 'achieving goals' (Item 2) and 'improving retention' (Item 7) compared to the others.

Another survey question asked all the participants (n=45) to rank the importance of various elements that might affect achieving the potential of LA in their institution using 5-Likert scale (1 being 'not at all important' and 5 being 'critical') (Figure 5). The results show that the respondents were generally in agreement with all the statements, though the following items were considered critically important by many: 'senior manager buy-in' (Item 1), 'teaching staff/ tutors buy-in' (Item 2), 'legal framework' (Item 12), 'privacy protection' (Item 13), and 'ethics guidelines' (Item 14).

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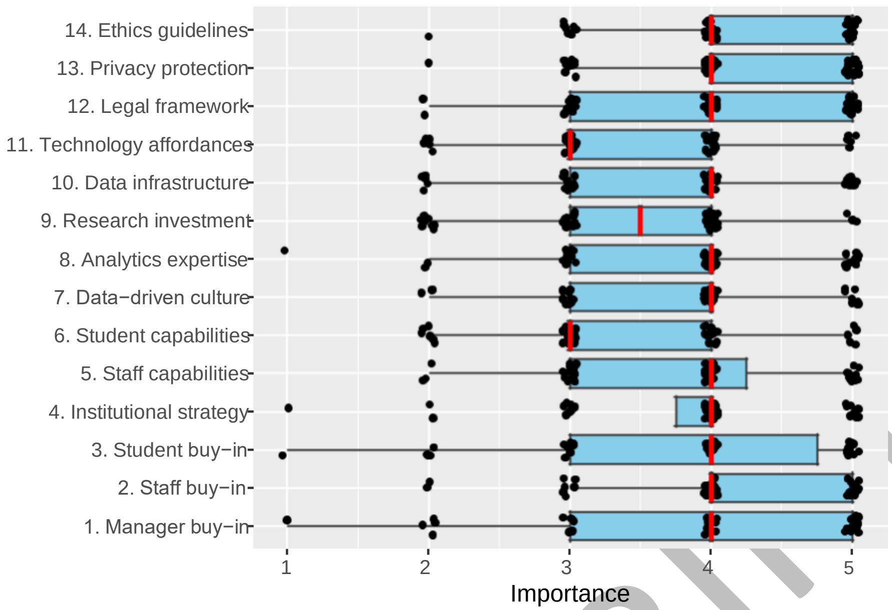

Figure 5: Important elements to achieve LA potential. Medians are denoted by the red solid lines, boxes represent interquartile ranges (IQR), whiskers are 1.5 IQR, and data points are marked with grey dots. Answers to N/A are not counted. Full descriptions of items are as follows: 1. Senior manager buy-in, 2. Teaching staff/ tutors buy-in, 3. Student buy-in , 4. Institutional strategy, 5. Staff capabilities to understand analytics results, 6. Student capabilities to understand analytics results, 7. A data-driven culture at the institution, 8. Analytics expertise, 9. Investment in research related to learning analytics, 10. Current infrastructure for data storage and management, 11. The affordances of current technology, 12. Legal framework, 13. Privacy protection, and 14. Ethics guidelines.

However, high variations are observed when it comes to 'senior manager buy-in' (Item 1), 'student buy-in' (Item 3), and 'legal framework' (Item 12). It is also notable that 'student capabilities' (Item 6), 'research investment' (Item 9), and 'technology affordances (Item 11) were considered less important by several participants compared to the other items. Similar to the observation of imbalanced involvement between teachers and students as presented in the previous sections, when comparing staff buy-in (Item 2) versus student buy-in (Item 3) and staff capabilities (Item 5) versus student capabilities (Item 6), the respondents generally attributed higher importance to the former.

4.2. Barriers to institutional adoption of learning analytics

In terms of barriers to the success of LA, survey respondents (n=45) were invited to rank 13 items using a 5-Likert scale (1 being 'not a barrier' and 5 being 'a critical barrier') (Figure 6). The results show that responses to these items are polarised in general. However, views of analytics expertise (Item 7) were leaning towards large or critical barrier. In contrast, views of institutional strategy (Item 4) and staff and student capabilities' (Item 5) were leaning towards small or not a barrier. Interestingly, despite the comparatively positive views towards institutional strategy here and the importance attributed to it (Figure 5), there is a notable gap in terms of implementing LA with a clear strategy as discussed earlier (Section 4.1.3). It also appears that views towards senior manager buy-in (Item 1) and legal framework (Item 11) in terms of being a barrier vary greatly among the respondents.

In contrast, 7 themes emerged from the interview data with regard to challenges of adopting LA: (1) ethics and privacy, (2) capabilities, (3) data limitations, (4) resources, (5) buy-in, (6) methodologies, and (7) relevance (applicability & usefulness). Among these themes, the four most commonly identified challenges across institutions are 'resources' (n=43), 'ethics and privacy' (n=39), 'buy-in' (n=36), and 'capabilities' (n=32). It is also found that re-source challenges were often associated with buy-in and capabilities in addition to funding constraints. For example, two respondents commented on the issue of expertise silos and the tension between workload and buy-in respectively:

> *There is technical expertise, but not especially in learning analytics. The people who have more knowledge about learning analytics are from the research groups of the university, but they are not technical staff in*

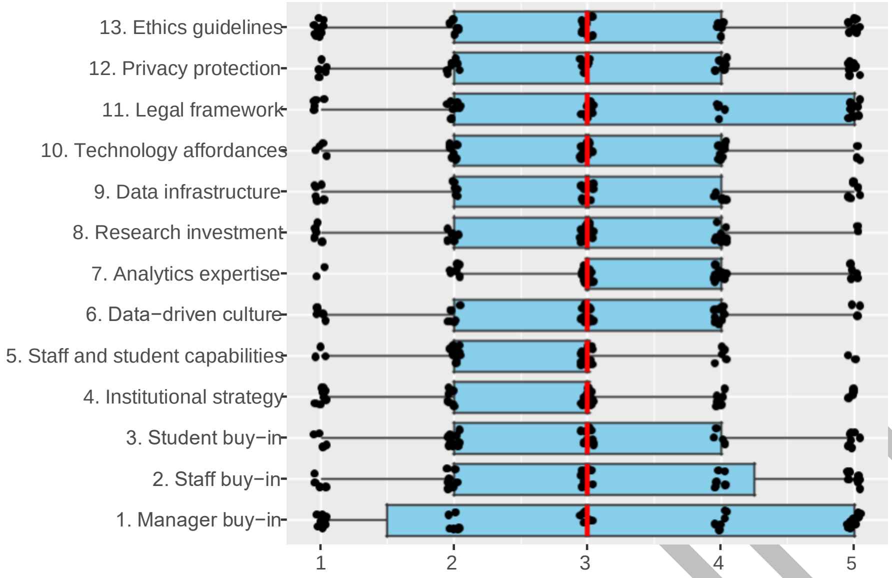

Figure 6: Barriers to the success of LA. Medians are denoted by the red solid lines, boxes represent interquartile ranges (IQR), whiskers are 1.5 IQR, and data points are marked with grey dots. Answers to N/A are not counted. Full descriptions of items are as follows: 1. Senior manager buy-in, 2. Teaching staff/ tutors buy-in, 3. Student buy-in, 4. Institutional strategy, 5. The capabilities of staff and students to understand learning analytics results, 6. A data-driven culture at the institution, 7. Analytics expertise, 8. Investment in research related to learning analytics, 9. Current infrastructure for data storage and management, 10. The affordances of current technology, 11. Legal framework, 12. Privacy protection, and 13. Ethics guidelines.

the central service of the institution. – U18 (Spain)

It [LA] would not succeed unless people were convinced in all of those [stakeholder] groups that this was actually going to be a benefit, because there is so many other pressures on people and so many other priorities. – U07 (Ireland)

On the other hand, support from senior management is key to resource allocation:

There is a lot a building blocks that you need to put in place, and those building blocks require buy-in from our senior management. – U44 (UK)

In a learning analytics policy, you need real people involved in real projects with real money in order to develop them in a successful way [...] With no extra fund, I think the learning analytics policy will be dead. – U17 (Spain)

The second most frequently mentioned barrier is related to ethics and privacy. The participants were generally highly aware of ethical and privacy implications associated with LA, especially the changes to existing data practices under the European General Data Protection Regulations 2016/679 (GDPR) (The European Union, 2016). While striving to use LA to enhance educational quality, a number of participants also perceived existing data regulations as barriers to fully utilising LA.

We have the problem that in general we are allowed to do nothing because it is privacy issues and it is the data of the students [....] even if both systems are located at the same university. We have identification, we would be able to combine it but we are not allowed. – U01 (Austria)

All these systems have to go to an audit, privacy audit, which is held by a commission on data protection. Each university, each institution has such a commissioner and that is the main obstacle for implementing data, analyzing tools, data collection tools, and so on. – U05 (Germany)

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Overall, the interview data revealed that the institutions were particularly wrestling with social issues rather than technical.

5. Discussion

This exploratory study consulted HEI leaders to understand the state of LA adoption in European HE. Although the study suffers from a self-selection bias, i.e., institutions that had taken interest in LA were more likely to respond to our survey and interview invitations, it is clear that the uptake of LA was at an early stage where the implementation among the interviewed institutions was primarily at small scales and few institutions had a dedicated strategy, policy, or evaluation framework for LA. Not only did the survey identify a driver to 'explore what LA can do', but the interviews also revealed that several institutions were piloting LA to consolidate an adoption strategy, and that most success to date was associated with the improvement in experience, knowledge, and attitudes.

A number of challenges associated with LA adoption were identified in the study, and the majority of these are rooted in tensions that occur when institutions strive to explore innovative ways to adapt to a changing environment while retaining their efficiency and accountability. Overall, an institution's capacity for LA is defined by a combina-tion of resources available including skills, funding, infrastructure, and people, in addition to a culture of using data responsibly to inform decisions. For senior managers, a common approach to addressing resource constraints is inte-grating LA into existing practices that support the institution's wider strategy. In other words, when institutions are in the 'learning phase' (i.e., exploring and experimenting with LA), it is crucial to have key leadership that can navi-gate and negotiate existing resources to encourage change and nurture innovations (Tsai et al., 2019). Take U42 (UK) for an example – the institution successfully implemented a university-wide project within one year under prominent leadership of a coalition of the Head of Learning Technology, Chief Information Officer, and Pro Vice-Chancellor in Academic and Student Experience. As part of the university's strategy to enhance student retention and success, U42 appointed an educational expert to drive effect change, which includes implementing LA along with other initiatives, articulating the purpose of LA and providing training to scale up staff's data literacy, forming a working group for LA, and developing a policy to govern the use of LA in the institution. Although this approach proved to be effective in terms of distributing resources, a notable challenge, according to the interviewees, was the difficulty to evaluate the success of LA due to a mix of factors introduced by multiple projects that shared the same goal – improving student retention and success.

Another key finding is that for senior managers the priority of LA deployment was to influence institutional and teaching decisions. The participants were particularly concerned about addressing common performance indicators such as student achievement, retention, satisfaction, and staff performance. This desire is evident not only in the moti-vation to adopt LA, but also the evaluation process. Not surprisingly, when asked about implementation outcomes in the survey, the effectiveness of LA as a solution to existing problems and as evidence to influence institutional decisions received the highest agreement among the participants. However, the study also identified teaching and support staff as the main users of LA and the main stakeholders involved in the implementation process. This has resulted in a focus on providing training for staff and addressing buy-in issues among this group of stakeholders. Although the ultimate goal of LA is to support learners and optimise learning (Long et al., 2011), the lack of engagement with students in the implementation process is notable in this study. The observed optimism about student capability to make use of data to support learning should also be challenged along with the myths of the digital native (Kirschner & De Bruyckere, 2017).

This particular finding has important implications regarding current conceptualisation of LA and directions for practice and research. By focusing on teaching and support staff (e.g., tutors, advisors, and counselors) as primary users, institutional leaders appear to perceive teaching and learning support as the main factors of learning experience and educational outcomes. As a result, LA is primarily perceived as a solution to challenges in teaching whereas its potential in helping students develop self-regulated learning skills based on data about themselves is overlooked. This conceptualisation reflects a perception of feedback practice as the teacher's responsibility to compose useful and timely comments. Instead of seeing feedback as an interactive process, this conceptualisation down plays the importance of cultivating feedback literacy among learners (Carless & Boud, 2018; Carless, Salter, Yang, & Lam, 2011). As a result, efforts in enhancing feedback practice are focused on technical aspects such as timing and structure (O'Donovan, den Outer, Price, & Lloyd, 2019), while neglecting other key factors of feedback experience such as student attitudes towards feedback and their ability to seek, understand, and use feedback (Henderson, Ryan, & Phillips, 2019). As LA has the potential to decentralize teaching and learning, it is important to develop self-regulated learning skills and data

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literacy through a partnership relationship between learners and teachers. It is also worth noting that the experience of being in the learning process places learners in the best position to describe learning needs and struggles in addition to fill in the missing gap of data that is not capturable (Schumacher & Ifenthaler, 2018). We argue that it is important to give a voice to both teachers and students in shaping the development of LA (Holstein, McLaren, & Aleven, 2019) so as to scale the impact of LA on 'optimising learning' (Long et al., 2011).

This study also raises a question as to the extent to which current deployment of LA has been informed by learning sciences. Although the importance of grounding LA in educational theories and pedagogical practice has received wide recognition in research (Gašević et al., 2015, 2017; Herodotou, Rienties, Boroowa, et al., 2019; Jivet et al., 2018; Kitto, Shum, & Gibson, 2018; Matcha et al., in press; Schmitz et al., 2017; Wise & Shaffer, 2015), the absence of strategy specific for LA among the institutions that we have consulted makes it unclear to what extent LA practices have been informed by the pedagogical expertise owned by teaching staff, despite the high involvement of teachers as key stakeholders and users. From a pedagogical point of view, the observed learning patterns are meaningful only when the captured data and chosen indicators match with instructional design (Corrin, Kennedy, & Mulder, 2013; Lodge & Corrin, 2017; Pardo et al., 2019). Thus, having a mechanism in place to ensure that LA aligns with learning theories is crucial to effective adoption. Interestingly, we noted a comparatively lower degree of importance attributed to investment in research on LA in the survey results (Figure 5). As our analysis of existing adoption frameworks has shown (see Section 2.3), pedagogical grounding as a challenge of LA has not received its due attention, and we thus call for researchers and practitioners to consolidate this area of work. For example, the frameworks proposed by Herodotou, Rienties, Boroowa, et al. (2019); Prieto et al. (2019); West et al. (2016) can be useful to facilitate constructive dialogue between different stakeholders, though we suggest future research and practice to adapt these frameworks to include students as a key stakeholder in the dialogue, as Dollinger and Lodge (2018) have also emphasised in their research on co-created strategies for LA. Other adoption frameworks such as SHEILA (Tsai et al., 2018) and DELICATE (Drachsler & Greller, 2016) also provide comprehensive guidelines to ensure responsible and effective adoption of LA by including all the key stakeholders in the strategy and policy conversation.

6. Final remarks

LA promises to enhance education by providing insights that may otherwise not be obtainable without the availability of data and technology today. The main question that concerns us is, has the intervention of LA really enhanced learning, teaching, and the overall educational environment? How should we evaluate the impact and develop our ca-pacity to continuously learn and mature from the process of exploring the big question? In this paper, we have provided a glimpse of the current state of art in terms of the development of LA in European HE. LA has been an active research field for a decade, yet evidence of impact remains scarce (Ferguson & Clow, 2017; Viberg et al., 2018). We call for the HE sector and the LA research community to reflect on the discrepancy between our theoretical understanding of LA and the conceptualisation of LA embodied in existing deployment approaches. In particular, we highlight the urgent need to address the imbalance between the involvement of teachers and students, in addition to ensuring the foundation of learning sciences in LA design and implementation. We acknowledge that the operational process of deploying LA in an institution may tend to involve certain stakeholders earlier than others. Our intention here is to promote an inclusive approach to ensure that a voice is given to all the relevant stakeholders.

7. Limitations

This paper aims to present a picture of the institutional adoption of LA in European HE. To this end, we focus on our consultations with senior managers in order to take advantage of their knowledge regarding the strategic decisions and actions related to LA. As a result, this paper is limited in the diversity of perspectives, and thus should be compared with the results of our wider study (blinded for review). As mentioned previously, the study presented in this paper suffers from self-selection bias. That is to say, institutions that participated in our study already took an interest in LA. Therefore, it is important to note that our claim regarding the development of LA in European HE is limited to a particular population explained above. Moreover, although our interviews are targeted at senior managers to obtain insights of their institutional approaches to LA, it should also be taken into consideration that the responses from our participants are based on their personal perspectives, observations, and experiences in their institution. As also indicated earlier, Spain and the United Kingdom are particularly active in the LA research field (Waheed et al., 2018), which is also reflected in the number of institutions attracted to our study. Therefore, although the study has

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successfully involved institutions from 24 different countries, the results presented here are skewed towards the two countries. A follow-up study on the development of LA may focus on capturing relevant activities in less represented regions. We also acknowledge that factors such as institutional size and experience with LA can impact institutional strategies. Due to the scope of this paper, we have not included these aspects, though it is our plan to explore these further in future studies.

8. Acknowledgement

BLINDED FOR REVIEW.

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