Learning Analytics in Higher Education – Challenges and Policies: A Review of Eight Learning Analytics Policies

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ABSTRACT
This paper presents the results of a review of eight policies for learning analytics of relevance for higher education, and discusses how these policies have tried to address prominent challenges in the adoption of learning analytics, as identified in the literature. The results show that more considerations need to be given to establishing communication channels among stakeholders and adopting pedagogy-based approaches to learning analytics. It also reveals the shortage of guidance for developing data literacy among end-users and evaluating the progress and impact of learning analytics. Moreover, the review highlights the need to establish formalised guidelines to monitor the soundness, effectiveness, and legitimacy of learning analytics. As interest in learning analytics among higher education institutions continues to grow, this review will provide insights into policy and strategic planning for the adoption of learning analytics.

CSS Concepts
•Applied computing → Education; •Security and privacy → Human and societal aspects of security and privacy

Keywords
Learning analytics, policy, code of practice, challenge, strategy, higher education

1. INTRODUCTION
While interest in learning analytics remains high among higher education institutions, some hesitate to embrace it due to various challenges regarding data procurement, institutional capabilities and buy-in from relevant stakeholders [13]. There are many unanswered questions with respect to the effectiveness and usefulness of learning analytics to specific institutional contexts and problems even for institutions that have taken initiative to adopt learning analytics [10]. This pervading uncertainty calls for an investigation into challenges faced by higher education institutions in their adoption of learning analytics, and into policies that are meant to frame the practice of learning analytics and ensure that it is effective and appropriate.

In light of this, this paper first reviews literature about the state of learning analytics adoption and related challenges based on 23 empirical studies of learning analytics (Section 4). This is then followed by a review of existing policies for learning analytics (Section 5) and a discussion on how the policies have addressed the identified challenges (Section 6), so as to provide insights into future policy development. In the context of this paper, 'learning analytics policy' is perceived as a set of guidelines that include both legislative regulations and non-legislatives principles for the use of learning analytics. Therefore, a code of practice for learning analytics is also considered a policy in this study.

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2. BACKGROUND
Educational institutions are complex adaptive systems, which tend to be stable and resistant to change due to a range of political, social, cultural and technical norms [17]. Therefore, the challenge to bring about change in higher education institutions where complex and adaptive systems exist has been described as a 'wicked problem' [17]. It is suggested that persistent, dedicated and strategic efforts are required for the adoption of learning analytics [3][26], which highlights the imperative to analyse challenges faced by institutions in their adoption of learning analytics so as to develop a comprehensive policy that is visionary, pertinent to the context, concurrent to the institution's mission, and addresses the challenges faced by the institution.

There have been approaches to learning analytics policy development, such as the cause-effect framework and the RAPID Outcome Mapping Approach (ROMA) [17][36]. The former is used to identify the relationships between multiple linkages in complex systems where step-by-step action is needed to bring about effect change. The latter contains seven steps: define (and redefine) policy objectives, map political context, identify key stakeholders, identify desired behaviour changes, develop an engagement strategy, analyse internal capacity to effect change, and establish monitoring and learning frameworks. This framework is meant to be used iteratively and reflectively so as to allow refinement and adaptation of goals and solutions. For example, Ferguson and others used the ROMA framework to analyse three institution-wide learning analytics cases, which gives a strategic view of the practice and suggests practical steps to consider at each phase of the ROMA cycle [13].

It is of great importance that institutions adopt learning analytics under clear guidelines that are grounded in cultural, social, economic and political contexts specific for each institution and are based on existing best practices for learning analytics and learning theories. However, there has not been much analysis of existing learning analytics policies, especially not with respect to how they address challenges that have emerged in the empirical literature on learning analytics adoption. This paper sheds light on existing practices and makes a call for more methodological, comprehensive and coordinated work by the community.

3. METHODOLOGY
In order to understand the state of learning analytics adoption and

challenges that higher education institutions face in implementing learning analytics and how existing learning analytics policies have tried to address these challenges, we searched relevant literature using simple key words including 'learning analytics' and 'policy or policies' in journals and databases that were well-known for their collections of learning analytics related research and educational research. Table 1 gives an overview of the sources that we have consulted. Some of the journals were included at a later stage when we conducted a "snowball" search by following up references cited in literature that we included at the initial stage. It was also at this stage that we were able to retrieve some learning analytics policies.

Table 1. Sources of the bibliographical research

Databases	SCOPUS, Wiley Online Library, ERIC, ACM, IEEE
Journals	Journal of Learning Analytics, Journal of Computer Assisted Learning, Journal of Educational Technology & Society, American Behavioural Scientist, Journal of Educational Technology & Society, The Information Society, Computers & Education
Proceedings	The LAK Conference
Organisational databases	LACE publications, EDUCAUSE library

After the first stage of automatic search using key words, we filtered out less relevant literature based on the titles and abstracts, using our selection criteria of topics and publication types (Table 2). We were then able to conduct a 'snowball' search with the remaining literature, as mentioned earlier, and examine papers using the same filter criteria.

Table 2. Filter criteria for the bibliographical research

	Topics	Types of publications
Included	Ethics and privacy, policies, institutional strategies, institutional readiness, institutional capacities, learning analytics, academic analytics	Research reports, conference proceedings, journal articles, book chapters, policy documents, all years of publication, English language
Excluded	Affordances of learning analytics models and tools, interventions on class or individual levels, approaches to analytics, studies not based in higher education institutions	PowerPoint presentations, blog articles, news articles, workshops

While topics included in the filter criteria were exclusive to the context of learning analytics, we decided to include literature that looked at "academic analytics" if they met two conditions: one of our interested topics was covered, and the insights learnt were applicable to discussions about learning analytics. In order to get an overview of institutional adoption of learning analytics, we excluded literature that examined technological frameworks for learning analytics or small scales of interventions that were not centrally supported by institutions. We also excluded literature that explored methods for data analysis and studies that were not carried out in the higher education context.

During the snowball phase of our bibliographical research, we identified four existing policies for learning analytics, including Jisc's "Code of Practice" [24], LACE's "DELICATE checklist" [11], LEA's Box's "Privacy and Data Protection Policy" [29], the UK National Union of Students' (NUS) "Learning Analytics: A Guide for Students' Unions" [18], and the Open University's "Policy on Ethical use of Student Data for Learning Analytics" [31]. Then we used the Google search engine to look for other learning analytics policies using the key words – "learning analytics AND policies", and manually examined individual cases that have been studied in the literature that was included in the second phase. We found three more institutional policies with these methods: Charles Sturt University's "CSU Learning Analytics Code of Practice" [9], Nottingham Trent University's "Use of Learning Analytics to Support Student Success Policy" [21], and the University of Sydney's "Principles for the Use of University-held Student Personal Information for Learning Analytics at the University of Sydney" [25].

The bibliographical research finished in July 2016 and rendered 71 pieces of literature, among which 25 were empirical studies, 38 were desk studies, and eight were policies for learning analytics. We conducted a systematic literature review on 23 empirical studies after we further filtered out two studies based on the degree of relevance to our research interest. The findings of the empirical studies are presented in Section 4, while the review of the analysis of existing policies is presented in Section 5.

4. RESULTS – STATE AND CHALLENGES IN LEARNING ANALYTICS ADOPTION

This review identified six prominent challenges among higher education institutions in terms of the adoption of learning analytics. We first present the findings related to the state of learning analytics adoption (Section 4.1) and then challenges identified in the empirical literature (Section 4.2).

4.1 The State of Learning Analytics Adoption

A review of the state of learning analytics shows that interest is high among higher education institutions, but adoption remains immature. In the context of the US higher education sector, learning analytics has been used to eliminate impediments to retention and student success, and to create personalised learning environments [6]. However, there is a greater interest in monitoring or measuring student progress than predicting learning success or prescribing intervention strategies [35]. Moreover, learning analytics remains an interest rather than a major priority at most institutions [5].

A similar phenomenon was observed in the Australian higher education sector. A study conducted by Colvin and others revealed that only 2 out of the 32 institutions under study reached the advanced stage – having evidence of implementation of multiple interventions or initiatives informed by data [10]. The rest of the cases were either at the preparatory stage of learning analytics or early stage of implementation.

The adoption of learning analytics in the UK higher education sector is also in its infancy. A survey (N=53) conducted by the Heads of e-Learning Forum – which includes heads of 130 UK-based universities – among their members discovered that 25 respondents did not implement learning analytics at all, 18 were working towards implementation, 9 partially implemented, and only 1 fully implemented learning analytics across their institution

[19]. Moreover, another study that took a qualitative approach to investigate the adoption of learning analytics in 12 institutions in the UK discovered that few interviewees were willing to claim significant outcomes from their learning analytics activities to date due to the nascent stage of learning analytics technologies and practice [23].

4.2 Challenges in the Adoption of Learning Analytics

In addition to technical challenges in data and system integration [5, 34], several studies have identified challenges related to strategic planning and policy. Six primary challenges have been identified:

- Challenge 1: There is a shortage of leadership capabilities to ensure that implementation of learning analytics is strategically planned and monitored.
- Challenge 2: There are infrequent institutional examples of equal engagement with different stakeholders at various levels.
- Challenge 3: There is a shortage of pedagogy-based approaches to removing learning barriers that have been identified by analytics.
- Challenge 4: There are insufficient training opportunities to equip end users with the ability to employ learning analytics.
- Challenge 5: There are a limited number of studies empirically validating the impact of analytics-triggered interventions.
- Challenge 6: There is limited availability of policies that are tailored for learning analytics-specific practice to address issues of privacy and ethics as well as challenges identified above.

4.2.1 Challenge 1 – Shortage of Leadership

Studies found that the maturity of learning analytics is closely related to the presence of leadership. Yanosky and Arroway identified the lack of advanced analytics-based projections and proactive responses to analytics results among the US higher education institutions, and claimed that this pattern had not changed since 2012 [35][8]. They attributed one of the causes to the shortage of dedicated leadership in that leadership was associated with higher-level analytics maturity. The lack of support of key leadership in learning analytics activities among higher education institutions in the USA was again identified in a recent report published by EDUCAUSE [5].

In the Australian study, Colvin and others observed a different degree of leadership commitment in two clusters of institutions. One cluster perceived learning analytics as a vehicle or tool for measurement or efficiency gains. The other cluster perceived learning analytics as a means to aid reflections on the connection between retention and antecedent teaching, learning and student experience factors [10]. The first cluster tended to lack reflections upon the relationship between implemented strategies and the development of organisational capacity for learning analytics, whereas the second cluster contained a higher degree of readiness factors, more mature strategy development, and more involvement of senior leadership. Although this study does not suggest that there is a lack of leadership in the adoption of learning analytics among Australian higher education institutions, Colvin and others stress that a strategic vision that responds to the needs of an organisation is critical for long-term impact. Furthermore, they argue that the development of strategic institutional capability is a key prerequisite for the growth of implementation capability for learning analytics and overall institutional uptake by staff members. The latter has been identified as one of the stoppers of learning analytics in that resistance to change is pervasive in higher education institutions [5, 17]. Therefore, the involvement of leadership and visionary implementation with considerations of the interests of various stakeholders is imperative to the development of analytics.

4.2.2 Challenge 2 –Shortage of Equal Engagement

Learning analytics distinguishes itself from academic analytics by the learner-centred and learner-concerned nature. However, few studies have tried to explore opinions of students regarding the use of their data for learning analytics or the impact on their learning journeys. Among these studies, Slade and Prinsloo's study looked at 300 posts from the University Students' Consultative Forum to understand students' views regarding the use of their data for learning analytics [28]. Similarly, two publications by EDUCAUSE present both positive and negative views of students at Purdue University regarding the impact of a learning analytics project – Course Signals – on their learning [4, 27]. Unfortunately, neither of these publications offers clear descriptions of the methods adopted to collect and analyse student opinions. Another study by Drachsler and Greller made an attempt to engage students to explore the current level of understanding and expectations towards learning analytics among relevant stakeholders [11]. However, returns of the survey from students were few due to possibilities of uneven distribution among the stakeholders and exclusive dissemination channels. This study flags the top-down bias that exists in current research on learning analytics and the need to engage students strategically.

In addition to proactive engagement with students, sound communication between other stakeholders to establish common understanding of learning analytics and institutional readiness still needs facilitation. Oster and others investigated factors that influenced institutions' evaluations of their readiness to implementing learning analytics [22]. Their study discovered that information officers tended to give higher rating to an institution's readiness than other roles within the institution. Their explanation is that technology professionals have daily interaction with institutional data in various ways from collection to management and reporting, and hence their familiarity with and comfort working with data may have led to discrepancies in the view of institutional readiness when compared to other stakeholders in their institutions. As a result, Oster and colleagues suggest that bridging perceptions among stakeholders within an institution is critical to ensure a cohesive and collaborative implementation. Similarly, the Heads of E-Learning Forum (HeLF) conducted a survey on the adoption of learning analytics in the UK higher education, and 41 of the 53 respondents (Heads of e-learning) indicated that there was limited understanding about the possible benefits and outcomes of learning analytics across their institutions, while 4 suggested 'no understanding at all' [19]. In addition, this question received 13 free text comments, among which all but one referred to different levels of awareness and understanding within and across departments. Particularly, teams within technical areas had the greatest understanding. The aforementioned studies reveal the gap of understanding between different stakeholders within one institution, which could potentially become an obstacle to the institutional embrace of learning analytics.

4.2.3 Challenge 3 – Shortage of Pedagogy-based Approaches

Although learning analytics is claimed to have a great potential in reforming the way people learn and the way teaching is delivered, pedagogical approaches are not always considered as part of the strategy for learning analytics. For example, Macfadyen and Dawson investigated the extent to which an institution has informed decisions based on analytics results [16]. They found that the institution was prone to addressing technical challenges while the development of pedagogical plans was ignored. Another study exploring what influenced the beliefs of educators concerning the adoption of learning analytics tools identified the weakness of learning analytics tools to move from spotting student weakness and risk levels to providing pedagogically informed suggestions [1]. Despite the fact that the overall perception of the usefulness of learning analytics was positive among the participants, the only variant that was found to have a significant relation with the intention to adopt LA tools was when the educator encountered learning contents that needed improvement. Similarly, Dyckhoff found that teachers were particularly concerned with how teaching tools correlate with learning behaviours and outcomes [12]. She suggested that the design of a prototype for an exploratory learning analytics tool must differentiate learning offerings that the tool can afford. The abovementioned studies highlight the importance to consider pedagogical requirements and solutions in the design of learning analytics tools and projects.

4.2.4 Challenge 4 –Shortage of Sufficient Training

Shortage of skilled people has been identified as one of the elements in gaps between needs and solutions in the adoption of learning analytics [20]. For example, a pilot survey that examined readiness for learning analytics among nine institutions in the USA found that one of the respondents'[1] greatest concern is the lack of analytics ability among the staff [3]. The skill shortage makes it hard to move learning analytics towards an institution-wide scale. Goldstein and Katz explored the characteristics of institutions that claimed to have achieved success outcomes from the use of analytics systems, and discovered that the effectiveness of an institution's training programme and present staff skilled at analytics were key to the success [14]. Wasson and Hansen advocate that relevant training opportunities should be offered to all relevant stakeholders to improve understanding of learning analytics and equip them with skills to operate the tools and interpret data [32]. This can potentially bridge the gap in understanding and capabilities of learning analytics among different stakeholders, as identified in challenge 2.

4.2.5 Challenge 5 –Shortage of Studies Empirically Validating the Impact

Establishing successful cases has been identified as a requirement to persuade senior staff who can allocate budgets to support learning analytics [19]. However, it has been identified as a challenging task to evaluate the success of learning analytics or demonstrate advanced employment of learning analytics. The reason for this is attributed to the fact that the majority of higher education institutions that have taken initiatives to adopt learning analytics, are still in a preparatory or early stage [23][10]. Moreover, the lag time required to measure the effects of analytics-triggered interventions has made access to learning analytics outcomes even harder [5]. So far, success claimed for learning analytics has mainly been based on data collected during a short period of time. For example, a study collected data from four institutions during the 2012 spring semester found a significant difference in mean course grades between groups of students that had received interventions and those that did not [7]. While the size of data is significantly large and useful to obtain preliminary insights, the study is not able to demonstrate long-term impacts or sustained effects brought about by analytics-triggered interventions.

4.2.6 Challenge 6 –Shortage of Learning Analytics Specific Policies

While institutions generally have regulations regarding the use of data, the ambiguous and divergent views towards ethical issues across countries has created much difficulty in the development of learning analytics frameworks, and hence impeded the advancement of learning analytics [15]. In light of this challenge, Drachsler and Greller created an eight-point checklist named DELICATE, in order to facilitate a trusted implementation of learning analytics [11]. However, a survey conducted by the aforementioned Heads of e-Learning Forum in the United Kingdom revealed that principles around the ethical use of data for learning analytics as well as codes of practice were mainly under consideration with very few institutions having addressed these issues to date (13 out of 53 UK-based institutions – that responded to the survey – claimed to have considered principles and best practices around the ethical use of data, and 5 out of 53 institutions have adopted a code of practice) [19]. The results of this UK report show that current practice of learning analytics at higher education institutions lacks clear guidance that is designed for learning analytics-specific practice.

Another key element in learning analytics policies is strategy, which allows leaders to purposefully, tactically, and continuously move projects towards their goals [2, 20]. Macfadyen and Dawson advocate 'visionary data analysis'; that is, to present data in a logical way which highlights progress and room for growth against a backdrop of institutional targets [16]. They believe that learning analytics data needs to be presented with consideration of the socio-technical sphere in order to motivate organisational adoption and cultural change. The idea that learning analytics need to be implemented under a strategic vision that responds to the needs of an organisation concurs with arguments made by Colvin and others, as mentioned earlier [10]. Further, Ferguson and others promote the RAPID Outcome Mapping Approach (ROMA) as a framework for learning analytics to achieve learning and teaching goals [13]. It is recommended that a policy that ensures the practice of learning analytics to be legal, ethical and strategic should be installed in every higher education institution.

The six challenges identified in the literature highlight the fact that learning analytics need to be implemented with considerations of multiple dimensions that include institutional contexts, stakeholders at various levels, pedagogical applications, institutional capacities, success evaluation, legal and ethical considerations, and a strategy that aligns with the institutional missions. Thus, it is imperative that higher education institutions develop learning analytics specific policies or update existing policies to meet the requirements of learning analytics, and make them relevant to the institutional contexts and all stakeholders therein.

5. RESULTS – EXISTING LEARNING ANALYTICS POLICIES

The owners of the eight policies fall in two groups:

1. Support organisations and research consortiums:
   a. Jisc (a non-profit organisation that supports digital services and solutions in the UK higher, further education and skills sectors).
   b. LACE (Learning Analytics Community Exchange, an EU funded project which aims to integrate communities work-

[1] Respondents were involved in work related to learning analytics, data analysis, and research related to educational technologies.

ing on learning analytics and educational data mining from schools, workplace and universities).

   c. LEA's Box (an EU funded project which aims to create a learning analytics toolbox to enable a goal-oriented and proactive educational assessment that will provide formative support to learners).

   d. National Union of Students (NUS), UK (a confederation of 600 students' unions from more than 95 per cent of all higher and further education unions in the UK, committed to promote, defend and extend student rights).

2. Higher education institutions:

   a. Nottingham Trent University (NTU), UK

   b. The Open University (OU), UK

   c. Charles Sturt University (CSU), Australia

   d. The University of Sydney (USyd), Australia

In the following sections, we present these organisations' expectations of learning analytics and features of their policies. Then, we summarise key topics that have been covered by one or more policies including strategy, legal/ organisational obligations, privacy protection, data management and governance (3).

Table 3. Aspects of review

Dimensions	Aspects
Strategy	Goal setting, methods, evaluation of impact, assurance of validity, communication and support, and user roles
Obligations	Legal and organisational obligations
Privacy protection	Data anonymity, informed consent, and opt-out options
Data management and governance	Data handling process and access to data

Whenever applicable, the results are summarised based on points that are in common, in addition to tables that present additional points distinct to individual policies.

5.1 Expectations

While all of the eight owners of the policies acknowledge that the use of learning analytics must serve the purpose of enhancing learning, six of them explicitly state their expectations of learning analytics. They are summarised into four goals:

- Providing timely intervention
- Providing personalised learning
- Strengthening student-teacher relationships
- Developing a data-informed culture

5.2 Features of the Policies

While privacy protection and ethical use of data are of primary concerns to all, each of the eight policies is distinct in some features, which have shaped the emphases of these policies (Table 4).

Table 4. Features of the eight policies

Policies	Features
Jisc	The code of practice covers issues around data, responsibilities, interventions and adverse impacts of learning analytics. There is a particular emphasis on the effectiveness of learning analytics, which is reflected in the detailed suggestions for methods.
LACE	The policy is presented succinctly with eight principles that focus on dealing issues of privacy and ethics. It is known as the DELICATE checklist.
LEA's Box	The document is meant to balance individual privacy and beneficial uses of data when developing technological projects. It is part of a 44-page-long report, in which an overview of literature on ethical issues, privacy and data protection is included in addition to privacy and data protection regulations.
NUS	The policy is meant to state NUS' beliefs about proper practices of learning analytics and where they stand to defend students' right when issues arise. NUS adopts Jisc's Code of Practice for legal and ethical regulations.
NTU	The policy is developed specifically for the use of the student dashboard at NTU, and focused on methodologies that are adopted.
OU	The policy details the scope for and oversight on the ethical use of data in addition to the policy statement (eight principles). The policy statement is further developed into a page-long version for easy communication[2] with end users.
CSU	The policy contains seven principles grounded in relevant literature and a table of commitments that explains how these principles should look like in practice.
USyd	The policy contains eight principles that succinctly summarise the purpose, process, obligations, responsibilities, rights of students, and implications of learning analytics to students.

5.3 Strategy

Strategy identified in the eight policies comprises six components: goal setting, methods, evaluation of impact, validity assurance, communication and support, and user roles.

5.3.1 Goal Setting

With the exception of Lea's Box, all of the policies investigated explicitly define goals for learning analytics. JISC and LACE have stressed the need to set up goals but have not provided specifications for the goals, perhaps due to the diversity of the institutions in their partnership. While the rest of the policies all suggest that *enhancing learning and teaching* should be the ultimate goals for learning analytics, some provide additional information as to what learning analytics *should* and *should not* do (Table 5).

Table 5. The 'should' and 'should not' of learning analytics goals

Policies	Learning analytics should/ should not aim to…
NUS	Learning analytics must support the student-teacher partnership, which is at the heart of education.
NTU	Student dashboards should *enable* rather than *replace*

[2] The eight principles comprise a four-page-long publicity, called "Using Information to Support Student Learning".

	dialogues with students. It is not to be used for the purposes of assessment.
CSU	Learning analytics should enable "personalised management" of the relationship between the university and its students and employees. Moreover, it should provide input into decision-making for all the university staff.
OU	Learning analytics should inform institutional strategies to improve student retention and progression (macro level), and drive interventions and develop personalised learning paths (micro level).

Both NUS and NTU show concerns about student-teacher relationship, while CSU and OU highlight the goal of using data to inform decisions.

It is worth mentioning that CSU makes it clear that data generated by learning and teaching systems "will not be used as an official record of the University, and do not, in themselves, create an obligation to act" [9]. That is to say, the university holds the right to make the final decision in terms of the extent to which they will take action in response to analytics results. By contrast, OU states, "Where data indicates that there is potential for action to be taken which might better support students in achieving their study goals or in reaching their potential, the University has a responsibility to act on this" [31].

5.3.2 *Methods*

All the eight policies make suggestions on the methods that should be used to approach data, while some consider interventions, resources and the engagement with students. Table 6 summarises the methods.

Table 6. A summary of suggested methods

Suggested methods	Policies
The types of data that will be collected for learning analytics need to be stated.	All but NTU
The ways student data will be collected and used should be clearly explained.	All
The approaches to analysis and interventions should be explained.	Jisc
The circumstances for interventions should be specified.	Jisc, NTU, OU and CSU
Resources that will be allocated for learning analytics should be specified with consideration of students of different requirements	Jisc
The use of learning analytics should respect the differences between individual students.	OU and CSU
Bias or other adverse impacts may occur as a result of analytics, and such unintended results should be prevented by all means.	Jisc, OU and CSU
Students should be engaged actively in the adoption of learning analytics.	NTU, OU and CSU

The NTU policy encourages students to use student dashboards as a tool to reflect engagement with their studies. OU states that students should be engaged as active agents in the implementation so that students take responsibility for learning and the university can provide a more accurate interpretation of data and tailored interventions for individual students. Similarly, CSU suggests that students should be encouraged to be active "managers" of their own learning through the use of analytics, and interventions should be made under professional, sensitive and fair judgements while promoting student-centred practices.

5.3.3 *Evaluation of Impact*

There is generally a lack of plans for evaluating the impact of learning analytics in most policies. The USyd policy is the only policy that mentions plans to review their practice of learning analytics regularly to examine its relevance to the goal – enhancing learning experiences and outcomes. NUS states that they will continue to review the effects of learning analytics on policy issues and the public accountabilities of higher education institutions. Specifically, NUS object to any possibility of "datafication" of student behaviours and "dictatorship of data" in education.

5.3.4 *Assurance of Validity*

Many of the policies have made suggestions to enhance the validity of learning analytics in terms of data quality and comprehensiveness (Table 7).

Table 7. Considerations of data validity

Considerations of data validity	Policies
Learning analytics cannot capture or present a complete picture of a learning process.	All but LACE and USyd
Limitations of analytics must be revealed and inaccuracies should also be disclosed and minimised.	Jisc and Lea's Box
Learning analytics tools should allow the record of date stamps for new inferences or information so as to keep data updated and accurate.	LEA's Box

5.3.5 *Communication and Support*

Communication and support are essential elements to smooth implementation of any project within an organisation. While Jisc, LACE, and LEA's Box have not dealt with these aspects, NUS and the four universities have attended to them to different degrees (Table 8).

Table 8. Elements of communication and support

Communication and support	Policies
Students will receive support to resolve disputes encountered in their learning environments, and NUS members (officers and staff at higher education institutions) will receive assistance to engage with their institutions on learning analytics issues and defend students' rights.	NUS
The purpose, boundaries and methods used for the student dashboard, and the expectations of students to reflect on their own learning process using the dashboard should be communicated when students start the university (e.g., at induction or an early tutorial).	NTU
Learning analytics users need to be informed about how the results of learning analytics may affect them, and what their rights and obligations are.	OU and CSU
Staff and students will be provided with a set of guid-	OU

ance notes to engage them with learning analytics, and the university will provide training to develop the required skills across the institution.	
Students would be notified of any privacy breaches related to their information and would be informed of their rights as to how to make a formal complaint.	USyd

Although each of the four universities states that communication about the adoption of learning analytics needs to be in place, none of them mentions any two-way communication channels for different stakeholders to share ideas and experience to work together on learning analytics.

5.3.6 *User Roles*

In terms of the roles that users play in the implementation of learning analytics, Jisc, NTU, OU and CSU all emphasise that students should be treated as active agents with certain degrees of responsibility to manage their data, make decisions related to their learning, and engage with their studies. In addition, Jisc suggests that higher education institutions should specify the obligations for students and staff to act on analytics, and that staff should have sound working knowledge of the legal and ethical practice of learning analytics.

5.4 Legal/ Organisational Obligations

All of the policies were developed under the framework of national or international policies for data protection (Table 9).

Table 9. National and international data protection policies

Policies	Place	National/ International data protection laws
Jisc, NTU, OU, NUS	UK	- Data Protection Act 1998 (NUS adopts Jisc's Code of Practice)
LACE	Europe	- EU Directive 95/46/EC
LEA's Box	Europe	- Act No. 101/2000 Coll. (Czech Republic) - DSG 2000 (Austria) - Data Protection Act 1998 (UK) - 1995 Data Protection Directive (Directive 95/46/EC) (EU)
CSU, USyd	Australia	- NSW Privacy and Personal Information Protection Act 1998 (PPIPA) - National Statement on Ethical Conduct in Human Research (NSECHR) - NSW Health Records and Information Privacy Act 2002 (Only USyd)

In addition to the aforementioned laws, all universities consulted relevant policies existing in their institutions. Table 10 summarises those that were listed in the four policies.

Table 10. Institutional data protection policies

Institutions	Institutional data protection policies
NTU	- The University's data protection policy
OU	- The University's Teaching and Learning Policy
CSU	- CSU Privacy Management Plan and 19 other policies held in the CSU Policy Library
USyd	- The University's Privacy Policy 2013 - Privacy Management Plan - University of Sydney Act 1989

It is also worth noting that, with the upcoming application of general data protection regulations (GDPR) in 2018 [30], higher education institutions in Europe and UK are likely to have to update existing policies soon.

5.5 Privacy Protection

Considerations of privacy issues deal with identification of data, informed consent, and options to opt out of data collection.

5.5.1 *Data Anonymity*

Table 11 summarises the considerations of data anonymity in the eight policies.

Table 11. Considerations of data anonymity

Considerations of data anonymity	Policies
Any data collected for or generated by learning analytics must remain anonymous.	All but USyd
Data must remain anonymous when it is transferred between multiple sources and aggregated.	JISC, LACE, and LEA's Box
Whenever third parties are involved, special attention needs to be paid to data anonymity, and any data sharing needs to comply with privacy requirements in the current policy as well as institutional and national/international policies.	LACE, LEA's Box, OU, and CSU

Although the USyd policy does not explicitly mention data anonymity in its short list of principles, they point out that students will be appropriately notified about how their data will be disclosed, and the university will adopt appropriate safeguard to protect the security and integrity of university-held student information.

5.5.2 *Informed Consent*

All of the policies state that consent must be obtained before data is collected from students, and three provide additional information about the contexts of consent seeking (Table 12).

Table 12. Context of consent seeking

Contexts of consent seeking	Policies
Informed consent will only be sought at student enrolment.	NTU
Personal interventions also require consent from students.	Jisc
Whenever HTTP cookies are used in a learning analytics system, user consent should be obtained.	LEA's Box

5.5.3 *Opt-out Options*

Table 13 summarises the considerations of opportunities to opt out of data collection for learning analytics in the eight policies.

Table 13. Opt-out options

Opt-out options	Policies
Users should be given the option to opt out of the data pool or collection process.	All but NTU and USyd

Students can amend consent agreements on a periodical basis.	OU and CSU
Users should be able to opt out without any consequences.	LACE
Any potential adverse consequences as a result of opting-out of data collection must be clearly explained.	Jisc
Learning analytics mechanisms must allow a specific user's data to be withdrawn at any time.	LEA's Box

While the USyd policy has no mention about opt-out options, NTU clearly states that such an option is not available, and their justification says,

> *As part of their enrolment conditions, students give permission to the University to use and process data. It would not be possible to deliver courses or manage support for students without this data. It is therefore not possible for students to opt out from having their data in the Dashboard or other University core information systems* [21].

By contrast, OU and CSU offer the option to amend consent agreements on a periodical basis. However, it is not clear whether students are given the opportunity to amend their consent to existing data collection or to give consent to the collection of a new set of data. Unlike universities that are more concerned about data completeness, research consortiums offer more generic statements regarding data opt-out.

5.6 Data Management and Governance

A parallel issue to privacy concerns is data management and governance. The current review deals with the following aspects: the data-handling process and access to data.

5.6.1 Data Handling Process

Each of the eight policies deals with data handling to various degrees of detail, but all policies indicate that the process for handling student (and staff) data must be transparent, with clear explanation on ways such data will be used. Additional information about data handling is provided in Table 14.

Table 14. Considerations of data transparency

Considerations of data transparency	Policies
The methods used to collect data have to be disclosed to the subjects of the data collection.	LACE, LEA's Box, OU, CSU and USyd
The information about how data will be stored needs to be provided.	LACE and CSU
Users need to be notified about where their data has travelled in any integration process between multiple entities and informed about any changes made to the analytics process.	LEA's Box

5.6.2 Access to Data

All of the policies state that users should be given the right to access their own data that is held on institutional systems, and some (LACE, LEA's Box, OU, and USyd) explicitly indicate that users should be able to manage and update such data. Table 15 summarises considerations of data access in various contexts. The first four items focus on students' access, while the remaining four deal with the access to data by other stakeholders, including third parties.

Table 15. Considerations of data access

Considerations of data access	Policies
Learning analytics needs to be in forms accessible to students.	Jisc
Analytics facilities should be available to anyone to whom the service has been provided even if consent for the collection of their data is not given.	LEA's Box
Any metrics and labels attached to students must be revealed on students' request under the condition that no harmful impact results.	Jisc
Students should be given access to data on their learning in a way that i) enhances agency and autonomous learning, ii) promotes quality learning and engagement, and iii) recognises student diversity and individuality.	CSU
Different stakeholders will be granted access to data with different authorisation privileges as to the range of data that they can access.	LEA's Box and NTU
When external parties, including educational authorities, are involved, their access to student data needs to be clearly defined.	Jisc
Student data will only be shared with third parties under the circumstance that useful information in helping students can be provided.	NTU
Student data must not be sold or shared with commercial third parties.	NUS

6. DISCUSSION

In response to the six challenges identified in the literature, this section will examine whether and how the eight existing policies address these and provide a bigger picture of these challenges in the wider environment of higher education. Certain discussions will focus on the four higher education institutions alone.

6.1 Leadership Involvement and Learning Analytics Specific Policies

The fact that the four universities have developed institutional policies for learning analytics suggests that there is some degree of senior management involvement and support from the institutions. Moreover, the governing bodies of these policies will be responsible for ensuring that the practice of learning analytics complies with the guidelines for data management and with the goals to enhance learning and teaching. However, the fact that only four policies from higher education institutions were retrieved indicates some possible scenarios. First, most institutions either implement learning analytics without formalised guidelines or with guidelines that are not originally developed specifically to meet requirements of learning analytics or specific institutional contexts. Second, some institutions are at a nascent stage of adopting learning analytics, and they allow this pilot stage to be part of the process for policy development. Third, the adoption of learning analytics in some institutions is a grassroots movement, and it has not gained support from senior management yet.

6.2 Communications between Stakeholders

Thoughts that have been put into communications between relevant stakeholders in the eight policies are limited to practical aspects as to what, how and why data is collected. It is noticeable that this communication strategy is predominantly top-down. None of the policies proposed dynamic channels to allow two-way communication among stakeholders at different levels. Although the USyd policy states that students will be informed of their right to make formal complaints, this is limited to the communication of negative opinions. However, the exchange of positive and constructive ideas should also be valued, as this can lead to an understanding of best practices.

6.3 Pedagogy-based Approaches

None of the eight policies made an attempt to suggest any pedagogy-based approach that i) teaching staff may take in response to learning analytics results, ii) technology developers should consider when designing and developing learning analytics tools, or iii) institutions should consider when acquiring external learning analytics tools. Although teaching staff are expected to make decisions based on analytics results, it is not clear whether they have been involved in the selection of the best parameters to evaluate student progress or engagement, neither is it clear what alternatives teachers have when analytics results do not provide actionable insights into teaching design.

6.4 Skills for Learning Analytics

While institutions normally have general instructions on the use of learning analytics systems, NTU states that engagement with students in learning analytics needs to happen as early as when they start their studies at the university. As discussed earlier, Jisc, NTU, OU and CSU expect students to engage with learning analytics actively by managing their data and taking action based on analytics results. The emphasis on putting learning analytics in the hands of students highlights the need to develop 'data literacy' – the skill to accurately interpret and critique presented analysis of data [33]. However, among all the universities, only OU has promised to develop the skills required for learning analytics across the organisation. It is unclear what kinds of "skills" are considered as required though, and further discussion with input from learning analytics experts and system designers is required to increase institutional capacity for learning analytics.

6.5 Evidence of Effectiveness

Of the eight policies, only the USyd policy mentions the need to validate learning analytics outcomes against desired goals. Moreover, it is clear that all the policies have neglected the importance of evaluation of interventions introduced to learning or teaching design. The literature suggests that not many mature cases are available for evaluations on long-term impact due to the nascent stage of learning analytics [23][10][5][7]. This is reflected in the policies under current review.

Evaluation should be included as an integral part of a learning analytics policy regardless of the maturity stage of implementation, as it offers opportunities for institutions to learn from previous experiences. Some policy development methods have emphasised this element. For example, the RAPID Outcome Mapping Approach (ROMA) includes the development of monitoring and learning frameworks as one of its seven critical phases in policy development [36][17].

Moreover, a solid process of evaluation allows institutions to build successful cases to promote learning analytics not only within institutions, but also in the wider sector of higher education [35]. For example, two respondents in the study conducted by Newland and others suggested that case studies that demonstrate benefits of learning analytics would provide credible evidence for raising awareness and understanding among all stakeholders [19].

7. CONCLUSION

The review shows that the eight policies have not given enough considerations to the establishment of two-way communication channels and pedagogical approaches. Most of the policies also lack guidance for the development of data literacy among end-users and for evaluation of the impact and effectiveness of learning analytics. Nevertheless, the existing learning analytics policies have established some examples that are of value for reference, particularly for institutions that are planning to develop their own institutional policies for learning analytics. The review also confirms that one of the biggest challenges in the adoption of learning analytics is the lack of institutional policies that are developed specifically to guide the practice of learning analytics with considerations of an individual institution's own cultural, economic, political and technical context as posited in policy development approaches such as the ROMA Rapid Framework [17, 36].

It should be noted that the findings and recommendations presented in this paper are by no means all encompassing. A small subset of the retrieved policies was composed in a succinct style for efficient communication to their targeted audiences. It is not clear whether these institutions have more detailed versions of policies that are only available to internal stakeholders. We would like to encourage all higher education institutions to publish their policies for learning analytics, both in succinct and fully comprehensive formats. The former enables rapid communication with relevant stakeholders, while the latter can provide opportunities for further engagement and keep higher education institutions accountable to their students and employees. We would also like to encourage the community to create a common (Web) space where all such policies will be indexed and shared[3].

We acknowledge that gaps exist between policy and practice. For areas that these policies have failed to address, it does not necessarily mean that these organisations have neglected them in their practice of learning analytics, and vice versa. The intention of this review is to highlight areas policy makers can consider when updating an existing policy or developing a new policy for learning analytics, so as to ensure that the implementation of learning analytics is appropriate, effective and legitimate.

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