Enhancement Themes

Evidence for Enhancement:
Improving the Student Experience

Learning Analytics and Enhancement: A Discussion Paper

November 2018

Heather Gibson and Alan Clarke
The Open University

Contents

About this paper

This paper has been written for institutional managers and academics who are using, or wish to use, learning analytics to support the enhancement of the student experience. The aim of the paper is to help inform conversations with learning analytics experts in their institutions about some of the issues and challenges that are emerging from the learning analytics research field that may impact on institutional activities.

An overarching trend is the need to increase capacity for institutional staff and students to engage with ethics, design, understanding and using learning analytics. Where this has previously been the concern of a relatively small number of experts, it is becoming increasingly important that a broader community is equipped to participate in the conversation.

The paper is structured around an adaptation of Clow's 2012 cycle of learning analytics, and includes four key sections:

- data creation and collection
- working with and understanding data
- using data to enhance the student experience
- implementing learning analytics in institutions.

While the paper can be read in its entirety, each section is also intended to be a standalone text that can be used to stimulate discussion. Key literature is highlighted, and sections are illustrated with examples of practice. More examples of practice, including useful tools and case studies, are captured in two appendices.

Five 'Hot Topics' are identified: dashboard design, predicting the future, data capability, evaluating interventions, and linking learning design and learning analytics. Again, these may be used as standalone texts.

1. Introduction

This paper has been written for institutional managers and academics who are using, or wish to use, learning analytics to support the enhancement of the student experience. The aim of the paper is to help inform conversations with learning analytics experts in their institutions about some of the issues and challenges that are emerging from the learning analytics research field that may impact on institutional activities.

It assumes the reader will be familiar with certain artefacts and manifestations of learning analytics (for example, dashboards), and therefore discusses learning analytics in that context. The paper also seeks to situate learning analytics as an enhancement activity. This means that the paper does not delve into technical details or deal with detailed academic arguments, nor does it profess to be comprehensive. As Ferguson and Clow (2017) point out, the diversity of the field makes it 'impossible for any individual or team to keep up with all the literature'.

Learning analytics is a rapidly developing field, and the paper aims to provide a snapshot of some of the emerging practices and issues for learning analytics, for both researchers and institutions. For more detailed consideration and exploration of the field, the reader may wish to consult the SoLAR *Handbook for Learning Analytics*[1] and Niall Sclater's *Learning Analytics Explained* (2017). In each section of this paper, links have been provided to more detailed literature reviews that cover the topic in question.

The paper uses a variation of Clow's (2012) learning analytics cycle as a structure to locate how learning analytics is being used at present to enhance the student learning experience. Clow's cycle was chosen because it attempts to ground learning analytics in educational theory, emphasising the links between what can appear to be abstract numerical data and the nuances and subtleties of the student learning experience. The model also reflects a cycle of continuous improvement that was felt to align with the enhancement-led approach to quality in Scottish higher education. In any paper of this type, structure can be an artificial construct, and there are common themes that emerge from the different sections, which reflects the organic natures of the enhancement and the learning analytics worlds. However, it is hoped that the structure is useful and helps the reader navigate through the information.

Each section begins with a short introduction about the topic to set context. 'Hot topics' have been identified and are discussed in more detail. The 'hot topics' have been chosen either because they relate to enhancement priorities in Scotland or because they are of particular concern to the field at present.

What is learning analytics?

Learning analytics is a relatively new field of practice and research, with its first international conference (Learning Analytics and Knowledge or LAK) taking place in 2011 and the Society of Learning Analytics Research (SoLAR) being formed in 2012. The field is expanding rapidly: the most recent (2018) LAK conference in Sydney, Australia focused on engaging stakeholders in the 'design, deployment and assessment of learning analytics'.[2] There are a number of journals that regularly publish research work on learning analytics, and these are listed in Appendix B. A list of relevant organisations and projects working with learning analytics is given in Appendix C.

---

[1] solaresearch.org/wp-content/uploads/2017/05/hla17.pdf (13.4MB)
[2] solaresearch.org/core/companion-proceedings-of-the-8th-international-learning-analytics-knowledge-conference-lak18

As the field is still emerging, there is no standard definition for learning analytics, but rather a range of definitions. For the purposes of this paper, the following definition - developed by the Society of Learning Analytics - is used as a starting point:

> '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' (SoLAR, 2011).

Ferguson (2018), in her keynote presentation to the 15th Enhancement Conference noted: 'learning analytics help us to identify and make sense of patterns in the data to enhance our teaching, our learning and our learning environments'. The SoLAR definition could be amended to reflect the language of the Scottish enhancement approach:

> 'The measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and enhancing learning and the environments in which it occurs'.

Ferguson (2018) also notes that it is important that the data generated by learning analytics is acted upon, so the definition can be amended as follows:

> 'The measurement, collection, analysis, reporting and use of data about learners and their contexts, for purposes of understanding and enhancing learning and the environments in which it occurs'.

This definition reflects the cycle of learning analytics articulated by Clow (2012):

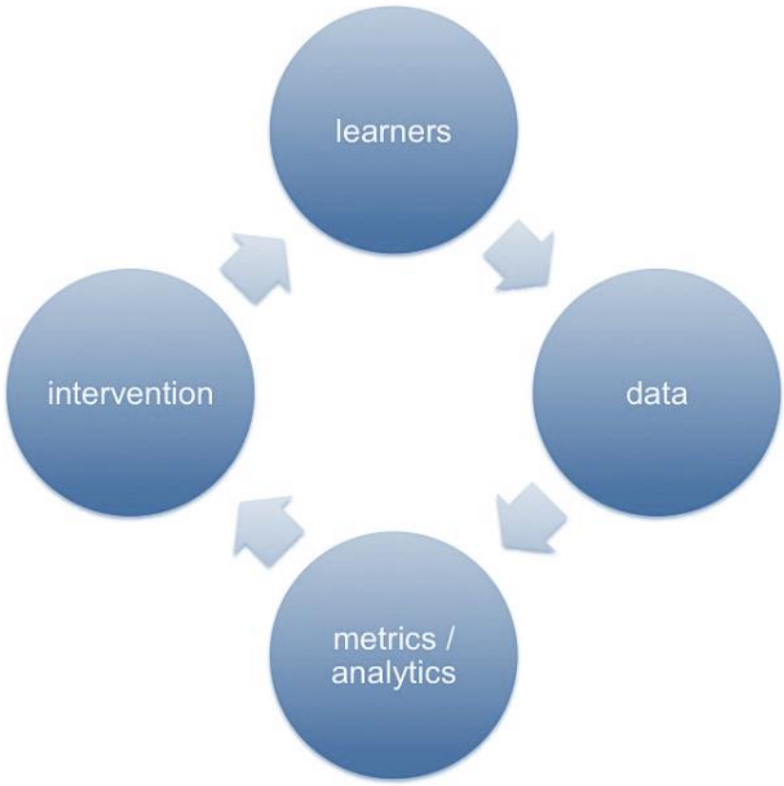


Figure 1: Learning Analytics Cycle (Clow, 2012)

The cycle reflects activity at four stages:

1 **Learners** creating data - this might be activity that constitutes part of a formal or non-formal course, or simply browsing learning material
2 **Data** - the capture of learner activity through interaction with virtual learning environments (VLEs) and other online systems
3 **Metrics/analytics** - analysis of the data, for example, to identify students at risk of failure or to provide insight for teachers or the learners through visualisations of the data
4 **Intervention** - to act on the data through some form of intervention to assist the learner.

The remainder of this paper is structured around a version of the above cycle that has been adapted to reflect the institutional processes that underpin these activities. Figure 2 represents the amended cycle.

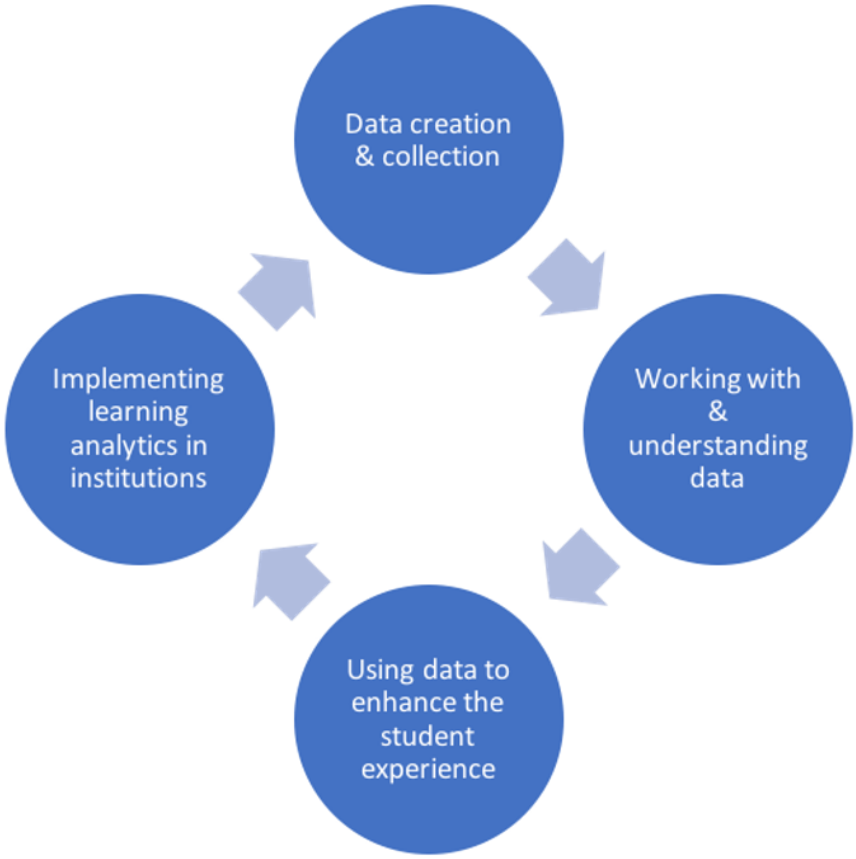


Figure 2: Clow's cycle as adapted for this paper

2. Data creation and collection

When learners interact with their institutional systems, their activity, communication and assessment is captured. Figure 3 below, based on a diagram created by Jisc, summarises a typical learning analytics system. The green shapes denote some of the data that is captured. These include:

- attendance data - at lectures, online tutorials, library usage
- assessment data - assignment scores, submission rates, dates of submission
- interactions with any VLE - pages accessed, how often these are accessed, repeated/return access, time of access, downloads, discussion forum use
- demographic information - age, ethnicity, gender, previous educational qualifications etc
- student records - modules studied, how fees are covered, location.

The model has two overarching aspects (identified as pink boxes) which deal with ethical issues. These are:

- students consent to the use of their data
- staff access to the data is controlled and managed so that student data is protected.

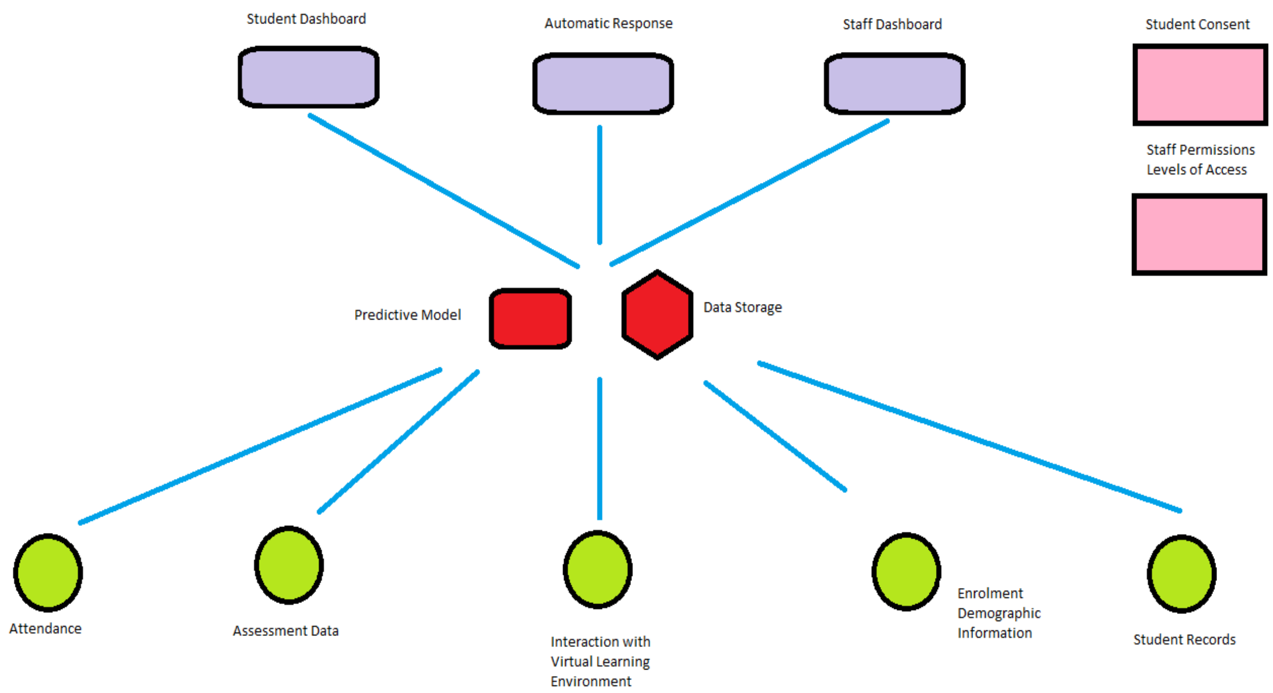


Figure 3: representation of how learning analytics can be structured (adapted from Jisc)

It is important to recognise that the potential of learning analytics comes with the need to consider the ethics of using personal data. As Sclater (2017, p 203) points out, the consequences for the student can be considerable: the algorithms used to create and present learning analytics data will influence the institution's and the students' (and potentially employers') perceptions of student success. At a societal level, the public's relationship with data and how it is used by large organisations is contentious. In his keynote presentation for LAK18, Selwyn (2018) makes the important point that for many people outside the field, 'the idea of learning analytics is an uneasy and sometimes controversial proposition', and that cultures of suspicion about data/technology in society have emerged that can be articulated through the messages: technology and data are not used for societal good, and the benefits of technology will not be equally shared across society. Perhaps the most important step for institutions to consider when implementing learning analytics is to work with all stakeholders to ensure that they know that the use of learning analytics data will be beneficial and ethical.

Ethics: it's not just privacy

Learning analytics involves collecting a great deal of data of all kinds from individual learners, including personal (and often sensitive) data as well as evidence of their engagement and performance. How institutions use that data responsibly, and how the rights of the students are protected in that use, is an area of ongoing concern. On a practical level, if ethical concerns are not addressed, or perceived not to be addressed, they can inhibit the use of learning analytics in an institution, as the risks for institutional managers may appear too high (see Sclater (2016), Drachsler & Greller (2016)). As Gasevic et al (2016) note: 'It is well recognized that these (ethical) issues lie at the very heart of the field and that great care must be taken in order to assure trust building with stakeholders that are involved in and affected by the use of learning analytics.'

Good review

Drachsler & Greller (2016) offer a thorough consideration of ethical and privacy issues and what can be done to address both. This paper also articulates the DELICATE Framework (see Figure 4, below).

Look out for: Sharon Slade (The Open University, UK) and Paul Prinsloo (University of South Africa).

Researchers in the learning analytics field agree that there is a need for more studies examining ethics and learning analytics (Ferguson & Clow, 2017). Viberg et al (2018) reviewed 252 papers covering learning analytics since 2011, finding that only 18 per cent of these mentioned ethics in relation to the research itself and that there were very few articles that considered ethics systematically. Similarly, Gasevic et al (2016), in the introduction to a special edition of the Journal of Learning Analytics on ethics, stated that more research was required. This is clearly an issue for the field to consider, and the Learning Analytics Community Exchange (LACE) project has an ongoing sub-strand of work looking at this: Ethics and Privacy in Online Learning (EP4LA). Among the work of this strand is the DELICATE framework (see Figure 4, below).

Issues for institutions

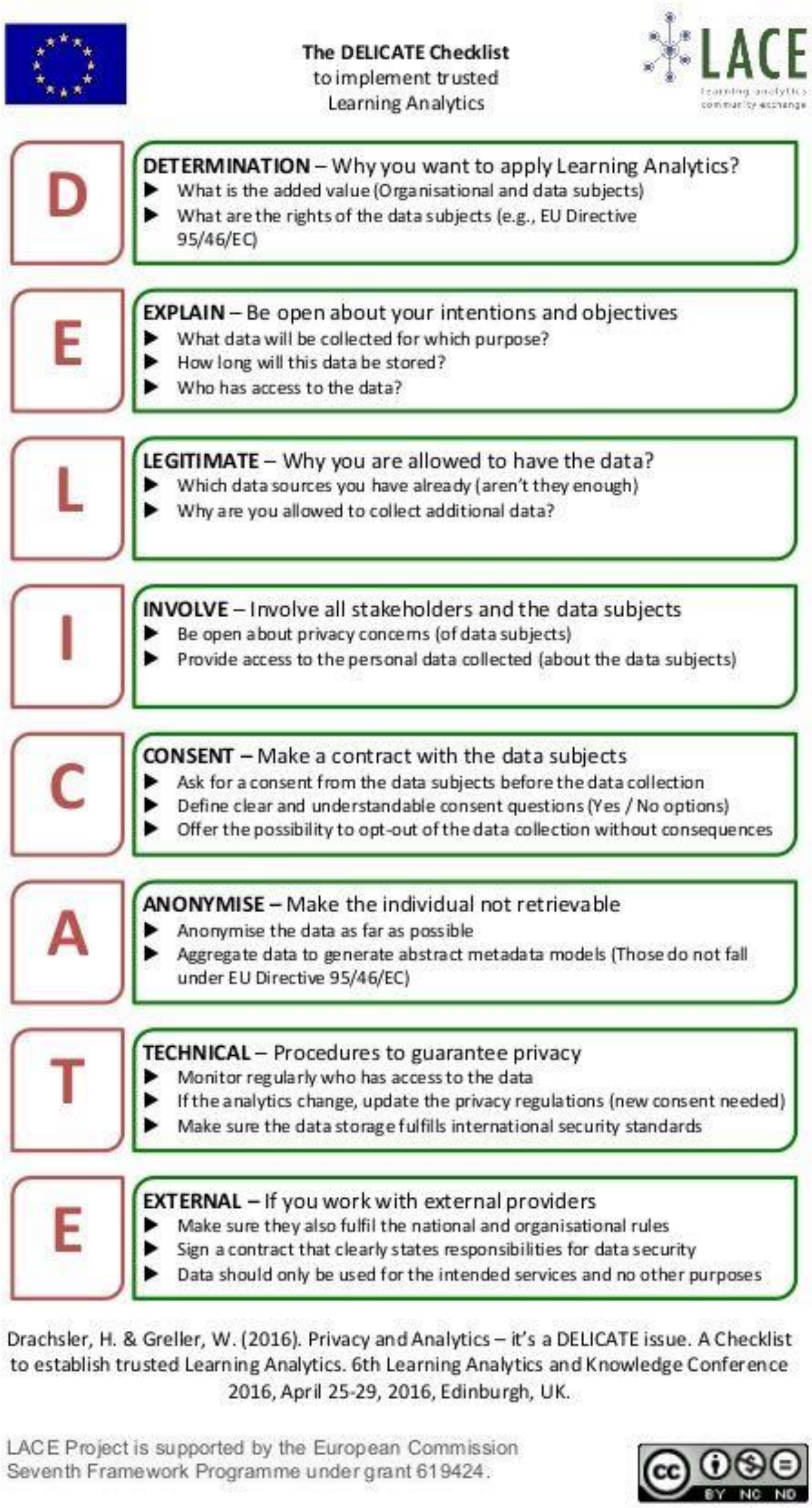
Slade and Prinsloo (2013) considered whether existing university policies covering the use of student information had kept pace with the development of learning analytics, concluding that in general they had not. Privacy is exercising staff in higher education institutions because of the recent introduction of General Data Protection Regulation (GDPR). To help institutions address GDPR, Jisc has provided information and advice to help institutions respond to the challenges.[3] Sclater also addresses some of the common questions

[3] www.jisc.ac.uk/guides/preparing-for-the-general-data-protection-regulation-gdpr

institutions may ask.[4] In summary, with regard to GDPR, institutions are encouraged to clearly explain to students *what* data is collected, *how* it is collected and *what* it is used for. In particular, institutions should articulate whether there is a lawful basis for collecting and processing personal data, that is, for the purposes of supporting students to succeed and to operate effectively. The Open University has developed a Student Privacy Notice[5] for this purpose and students are referred to this when they register on a course.

To help provide practical assistance for institutions to help develop policies to support ethical use of learning analytics, Drachsler and Greller (2016) developed a framework for institutions to use. This could be used to initiate and maintain the internal discussions within the institution that are needed in order to develop policy. The framework is called DELICATE, and Figure 4 presents it in more detail.

4 analytics.jiscinvolve.org/wp/2018/06/01/gdpr-and-learning-analytics-frequently-asked-questions
5 https://help.open.ac.uk/documents/policies/privacy-notice/files/47/student-privacy-notice.pdf (132KB)



The DELICATE Checklist
to implement trusted
Learning Analytics

D — **DETERMINATION** – Why you want to apply Learning Analytics?
- What is the added value (Organisational and data subjects)
- What are the rights of the data subjects (e.g., EU Directive 95/46/EC)

E — **EXPLAIN** – Be open about your intentions and objectives
- What data will be collected for which purpose?
- How long will this data be stored?
- Who has access to the data?

L — **LEGITIMATE** – Why you are allowed to have the data?
- Which data sources you have already (aren't they enough)
- Why are you allowed to collect additional data?

I — **INVOLVE** – Involve all stakeholders and the data subjects
- Be open about privacy concerns (of data subjects)
- Provide access to the personal data collected (about the data subjects)

C — **CONSENT** – Make a contract with the data subjects
- Ask for a consent from the data subjects before the data collection
- Define clear and understandable consent questions (Yes / No options)
- Offer the possibility to opt-out of the data collection without consequences

A — **ANONYMISE** – Make the individual not retrievable
- Anonymise the data as far as possible
- Aggregate data to generate abstract metadata models (Those do not fall under EU Directive 95/46/EC)

T — **TECHNICAL** – Procedures to guarantee privacy
- Monitor regularly who has access to the data
- If the analytics change, update the privacy regulations (new consent needed)
- Make sure the data storage fulfills international security standards

E — **EXTERNAL** – If you work with external providers
- Make sure they also fulfil the national and organisational rules
- Sign a contract that clearly states responsibilities for data security
- Data should only be used for the intended services and no other purposes

Drachsler, H. & Greller, W. (2016). Privacy and Analytics – it's a DELICATE issue. A Checklist to establish trusted Learning Analytics. 6th Learning Analytics and Knowledge Conference 2016, April 25-29, 2016, Edinburgh, UK.

LACE Project is supported by the European Commission Seventh Framework Programme under grant 619424.

Figure 4: the DELICATE Framework

This framework offers a series of prompts for institutions to use when considering work to develop a learning analytics ethics policy.

Another framework that might be useful to institutions is provided by Ferguson et al (2016), and identifies 21 learning analytical challenges related to ethics.

1	Use data to benefit learners
2	Provide accurate and timely data
3	Ensure accuracy and validity of analysed results
4	Offer opportunities to correct data and analysis
5	Ensure results are comprehensible to end users
6	Present data/results in a way that supports learning
7	Gain informed consent
8	Safeguard individuals' interests and rights
9	Provide additional safeguards for vulnerable individuals
10	Publish mechanisms for complaint and correction of errors
11	Share insights and findings across the digital divides
12	Comply with the law
13	Ensure that data collection, usage and involvement of third parties is transparent
14	Integrate data from different sources with care
15	Manage and care for data responsibly
16	Consider how, and to whom, data is accessible
17	Ensure data is held securely
18	Limit time for which data is held before destruction and for which consent is valid
19	Clarify ownership of data
20	Anonymise and de-identify individuals
21	Provide additional safeguards for sensitive data

Jisc offers a Code of Practice for learning analytics which covers many of the areas of DELICATE, as well as the challenges set out by Ferguson et al (2016). It emphasises privacy, consent, responsibility, validity, access, use and legality and sets out expectations for each.[6]

These frameworks, and the Jisc Code of Practice, provide a set of pointers to help institutions initiate and maintain the internal discussions necessary to ensure that learning analytics activity is carried out ethically. They can also act as a series of ethical touchstones, or act as an 'arbitrator' for different types of staff and students who may have different perspectives on what learning analytics should be used for.[7] However, it should be noted that any framework or policy will be a political construct, with values, agenda and messages determined by those who create it. This argues for increased involvement of all stakeholders throughout the institutional community in the creation and development of their learning analytics ethical frameworks.

There are valid reasons why policy development may not involve the entire institutional community and a policy may be developed centrally. However, policy implementation should be complemented by raising awareness and encouraging its use throughout the institution. As Gunn et al (2017) note: 'Policies and acceptable use guidelines need to be written and synergies between policy and practice encouraged'. One method of doing this can involve the construction of an institutional policy that is then used to inform other institutional

---

[6] www.jisc.ac.uk/guides/code-of-practice-for-learning-analytics
[7] ict-innovatie.uva.nl/2013/09/13/towards-a-uniform-code-of-ethics-and-practices-for-learning-analytics

policies, processes and practices. An example of an institutional policy that aims to do this is provided by the Open University. The original policy[8] is based on eight principles:

- 'Principle 1: Learning analytics is an ethical practice that should align with core organisational principles, such as open entry to undergraduate-level study.
- Principle 2: The OU has a responsibility to all stakeholders to use and extract meaning from student data for the benefit of students where feasible.
- Principle 3: Students should not be wholly defined by their visible data or our interpretation of that data.
- Principle 4: The purpose and the boundaries regarding the use of learning analytics should be well defined and visible.
- Principle 5: The University is transparent regarding data collection and will provide students with the opportunity to update their own data and consent agreements at regular intervals.
- Principle 6: Students should be engaged as active agents in the implementation of learning analytics (for example, informed consent, personalised learning paths, interventions).
- Principle 7: Modelling and interventions based on analysis of data should be sound and free from bias.
- Principle 8: Adoption of learning analytics within the OU requires broad acceptance of the values and benefits (organisational culture) and the development of appropriate skills across the organisation.'

These principles are then carried into University policy and practices, for example, principle 8 has generated activity within the University to increased data capacity and capability in staff, and the student privacy notice clearly sets out how and why the University collects student data (principles 2 and 5).

Learning analytics and ethics: looking deeper

Selwyn (2018) argues that education, technology, and learning analytics are political in nature: they are not value neutral, because they have been designed to produce particular societal and political effects. He encourages learning analytics researchers to consider some key questions:

- 'What is it you are actually doing?
- Why are you doing it?
- What are the key values, ideas, agendas and ideologies built into the design of the learning analytics/data you use?'

Higher education is also a political system. As Selwyn (2018) points out, from the early years to university, education has become more dependent on data and in tandem the use of data in education has become more contested. He argues that learning analytics has become part of the ongoing debate about what education is about. Is it just about learning? Should it focus on the individual good rather than the societal good? And so on.

At institutional level, Prinsloo and Slade (2016) note that there are intrinsic power imbalances between institutions and students and that there are dangers that students' vulnerabilities can be exacerbated even if the use of learning analytics is being used to address issues of equity and equality. The authors suggest that ethical debates should 'go

[8] help.open.ac.uk/documents/policies/ethical-use-of-student-data/files/22/ethical-use-of-student-data-policy.pdf (152KB)

beyond a simple 'rights' or 'privacy' perspective and explore the notion and scope of learner agency through vulnerability as a lens' (Prinsloo & Slade, 2016, p 166). This 'discursive-disclosure' approach allows what they call 'surveillance' to be located in 'the context of what is being done, by who, and for what purpose and then investigates alternative approaches to satisfy the need that initially resulted in the surveillance'. Like the questions raised by Selwyn (2018) above, the purpose for which data is being collected and used is articulated as a key concept, but this set of questions also considers who is collecting the data and encourages thinking around alternatives.

Both these references serve to emphasise that learning analytics operates in active social systems, and without careful examination of how these impact on the design and use of learning analytics, human biases (intentional or unintentional and from all stakeholders) can be inbuilt and exacerbated. The involvement of other disciplines in learning analytics such as political science, philosophy, educational research etc, will serve to hold a mirror to the discipline and help it develop a robust and ethical foundation.

The main message emerging from this brief discussion is that ethics is an ongoing concern for both the field and institutions, particularly in light of recent privacy concerns in other sectors and the introduction of GDPR legislation. However, it is clear that both the field and institutions are developing research, policy and processes to address ethics. More work could be done specifically around linking the field's work with institutional activity and concerns about student agency: for example, Prinsloo and Slade (2016) consider the issues of student agency and the potential for unintentional exacerbation of disadvantage through learning analytic work. Engaging with ethical concerns could stimulate discussion about the use of learning analytics in institutions - that is, the conversations that could arise as a result of considering ethics have the potential to unite different stakeholders and foster a sense of ownership. It is in the interests of everybody using and impacted by learning analytics that ethical issues are addressed.

As Gasevic et al (2016, p 2) note:

> 'We would like to take a different perspective to this and encourage the community to see ethics and privacy as enablers rather than barriers. It is natural that learning analytics stakeholders have serious questions related to a number of issues such as protection of their privacy, ownership and sharing of data, and ethics of the use of learning analytics. We would also like to posit that learning analytics can be only widely used once the critical factors are addressed, and thus, these are indeed enablers rather than barriers for adoption of learning analytics.'

3. Working with and understanding data

Vast quantities of information are produced by students engaging with online systems. Summarising and presenting that information in easy-to-understand and compelling formats can help users and decision-makers to interact with the data. Making the data more accessible can motivate users (including students) to design and implement interventions because it is easier to see where these may be most effective (Sclater, 2017, p 99).

The most commonly used tools by higher education institutions to visualise data are dashboards, which sometimes use predictive models. As most institutional policy managers and academics will be familiar with dashboards and predictive models, these are the tools discussed in this section. However, Appendix B has details of other tools that might be of interest.

Dashboards

Data is extracted from the various data systems in the institution, analysed, processed (perhaps through a predictive model) and the results summarised as tables, graphs and other data representation methods. What kind of data is extracted, how it is presented and whether it is used should depend on the identified needs of the user. Dashboards have been designed to summarise institution-wide data and key performance indicators, but they have also been designed to summarise data at module or individual level. Sclater (2017) discusses a tentative taxonomy for dashboards:

- module (performance indicators such as retention rates, demographic monitoring)
- pastoral (tutors looking at data for individual student performance and support)
- central support (institutional level, KPI).

It might also be apposite to add:

- student/learner (for students to monitor own performance).

Figure 5 illustrates an example of a dashboard summarising data for an individual student.

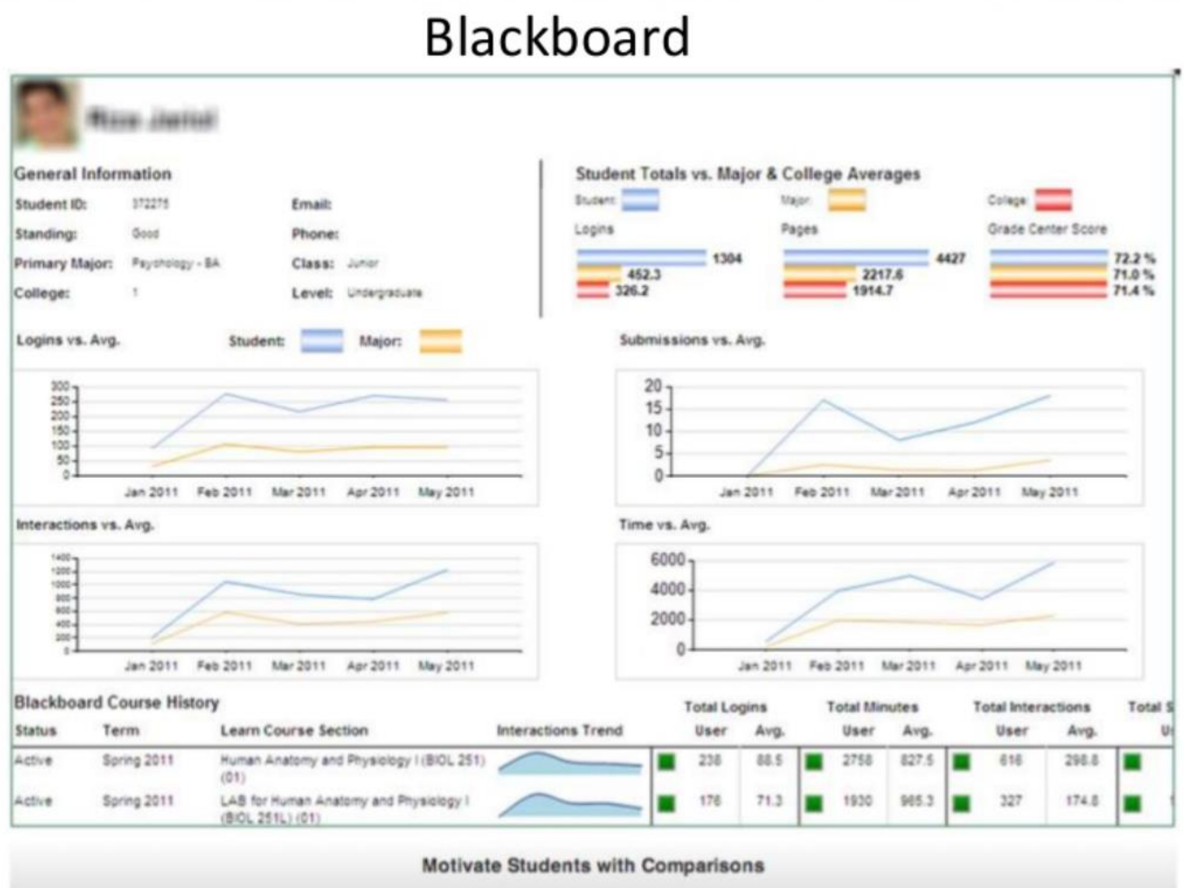


Figure 5: Learning Analytics Dashboard (Vozniuk, Govaerts, & Gillet, 2013)

Good review

Schwendimann et al (2017) carried out a review of research on learning dashboards that investigated the contexts dashboards were being used in, how well they were being evaluated, types of dashboards being used, and identifying any future directions research into learning dashboards might take. It is a very useful summary of work being carried out into learning dashboards.

Look out for: Ioana Jivet (Open Universiteit).

Hot topic: dashboard design

It is particularly important that institutional staff understand the data that is being presented to them, as they will use it to design interventions that will directly impact on the student learning experience. It is also important that they have the right data to help do this. Students need to understand what is being presented to them via dashboards so that they can monitor their performance and understand what they need to do to improve (student-facing dashboards in this context tend to focus on providing feedback on learning to students as their purpose).

Much of the work carried out in learning analytics around dashboard design has focused on student-facing dashboards. This might suggest an assumption that institutional staff understand what dashboards are telling them, this is an assumption that could perhaps be investigated in more detail.

However, there have been some insights from learning analytics about dashboard design for institutional staff. Sclater, Peasgood and Mullan (2016) reported that the New York Institute of Technology has developed a staff dashboard to assist staff to decide on what to do to support learners who were predicted to be at risk. The prediction identified correctly three-quarters of the students who would drop out. The dashboard allowed staff to be informed of the prediction in a timely manner so that they could take immediate action to help the individual learners. In this case, the dashboard was presented as a table with one line for each student and designed to be intuitive as possible. In addition, Webb and Bailey (2018) emphasise the importance of presenting information using terms with which tutors and students are familiar. Dashboard design therefore needs to take into account the needs of the user (what the user will use the data for), and the data capability of the user (the ability of the user to understand the data presented to them).

The current design of dashboards *for students* is probably best described as 'one-size fits all' (Jivet, 2018), with little consideration given to differences between learners, such as motivational factors. In a systematic literature review of papers looking at dashboard design for learners, Jivet et al (2017) identified that only approximately half the papers reviewed 'explicitly mentioned' some kind of pedagogical theory underpinning the design. These were categorised into six distinct types: cognitivism, constructivism, humanism, descriptive models, instructional design and psychological.

The paper argues for careful consideration for dashboard design for learners: what information is presented may communicate particular messages, which may or may not be helpful. 'Social framing' - learners being able to compare their performance against their peers - might promote the message that success is about 'being better than others' rather than about 'mastering knowledge, acquiring skills and developing competencies' (Jivet, Scheffel, Drachsler, & Specht, 2017). Comparing performance with others can be motivating for some learners, but not for others.

Bennett, presenting the results of a Society for Research into Higher Education (SRHE) study on learners' responses to dashboard design, offered a range of conclusions including that learner dashboards should:

1. recognise that learners are motivated by different factors
2. show individual learning routes and trajectories
3. allow learners to customise what information they can use and in what format
4. make it easy or explicit about how learners act on the information presented to them in the dashboard

(Bennett, 2018).

Knight et al (2015) address issues around stakeholders being involved in design by using participatory design (PD) to develop a learning dashboard for engineering students. This is best illustrated through Figure 6 below, which compares a 'traditional' dashboard design process (they describe this as 'for stakeholders' with the PD process (design with stakeholders)). Note the emphasis at all stages on interaction and discussion with relevant stakeholders.

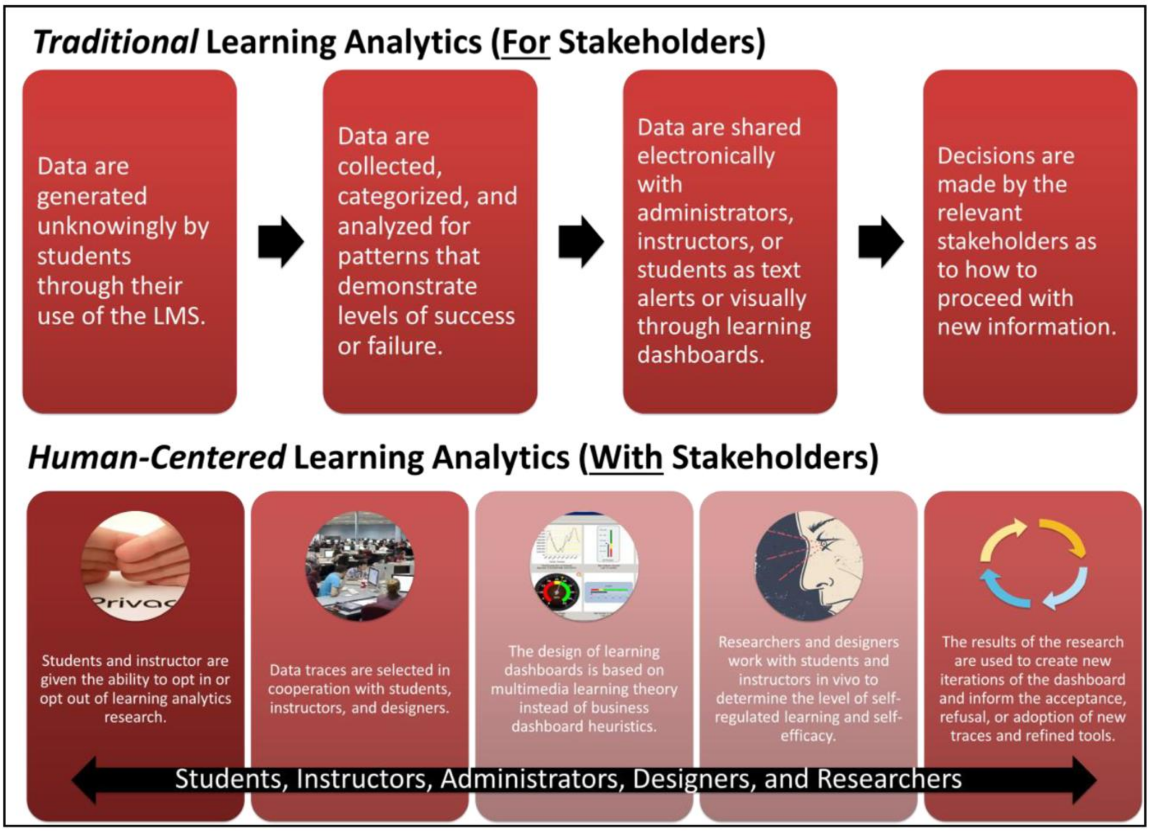


Figure 6: a participatory design framework (from Knight et al, 2015)

Participatory design is also identified by Gunn et al (2017) as being a 'powerful strategy to ensure that the sophisticated learning analytics tools that are the result of generous investment in research and development are actually fit for the users and purposes they are intended'.

Discussion about dashboard design must address accessibility for disabled students. Jisc highlights the need for all information presented on a dashboard to be offered in an accessible format so that a disabled student can use the data.[9] The design of visualisations needs to consider the use of assistive aids such as screen reader as well as the needs of other groups of students and tutors (for example, dyslexia).

These pieces of work emphasise the need to consider the needs of stakeholders and anticipate the potential effects (positive and negative) that presenting data in particular formats will have. Although these refer to students as the primary stakeholders, these comments are equally relevant to dashboards used by institutional staff for the reasons noted at the beginning of this section. Knight et al (2015)'s work which uses a participatory design involving stakeholders at all stages of the process, might be one way in which to address these issues. Like the other aspects of learning analytics discussed in this paper, the key message here is that for a dashboard to be fit for purpose, the design process needs to be opened up beyond learning analytic units to include the wider institution and student population.

[9] accessibility.jiscinvolve.org/wp/2017/01/09/an-inclusive-approach-to-learner-analytics

Predictive models

A very common use of data is to develop models that aim to predict student performance. Using predictive modelling can help institutions work with their data, identify those students particularly at risk, and target interventions that might help those students.

Predictive models are often complex, and are developed by using data collected about students' behaviours and performance. This data can be collected via VLEs, student record systems (including assessment), and interactions with other institutional systems such as library usage. Data may be static (demographic data, previous educational qualifications) or dynamic (engagement with the VLE and achievement (assessment, quiz scores)).[10] Different types of data have different strengths: because static data is relatively stable, it is used in many predictive models. Achievement data is used to measure student performance and dynamic data can yield valuable information about how students engage with course content and each other.

Figure 7 below details the data that was collected to form the probability model for the Open University's Early Alert Indicators Project (Gilmour, Boroowa, & Herodotou, 2018).

TABLE 1.

Student Probabilities Model	
Student Factors	Demographic factors including Disability, Occupation, Index of Multiple Deprivation.
Module study behaviour	Total numbers of credits being studied, late registration, proportion of assignments submitted to date.
Student's previous study	Credit transfer, previous educational qualification, sponsored or not
Student's previous progress at the OU	OU credit already achieved, number of previous OU passes, withdrawals or fails
Module within a qualification	Current module, study intensity of module, number of assignments due by milestone.

Figure 7: probability model developed by the Open University

Raw data like this is then used to produce metrics, quantitative measures that act as proxies for more complex behaviours. Metrics can be relatively simple, or more complex, but what is clear is that the more knowledge that informs a metric the more accurate proxy it will be. Therefore, metrics development may include qualitative information, such as pedagogical knowledge about curriculum requirements: a particular learning activity might support the acquisition of particular skills, or attendance at the library might be necessary to complete a task.

Metrics are then often subjected to statistical methods as part of creating the predictive model. Sclater (2017, p 88) notes three common methods: linear regression (relationship between two or more variables); logistic regression (relationship between two or more variables with the aim of calculating a probability of a student being at risk); and naïve Bayes (a type of probability analysis that assumes there is no relationship between variables, but that these variables 'contribute independently' to a probability that a student would be at risk[11]).

[10] library.educause.edu/resources/2015/10/the-predictive-learning-analytics-revolution-leveraging-learning-data-for-student-success
[11] blog.aylien.com/naive-bayes-for-dummies-a-simple-explanation

The outputs of predictive models are very often presented in dashboards, such as the traffic light system used at Purdue.

Figure 8: course signals system used at Purdue (Educause)

There are many other examples of predictive models being used in higher education, some of which can be found in Appendix A.

Sclater and Mullan (2017) identified evidence that suggests that predictive models do work to improve student outcomes and their report details some examples of this. The report noted that VLE engagement appears to predict student success much more effectively than student demographic factors.

Good review

Sclater (2017) provides an excellent and accessible summary of describing metrics and predictive modelling, including examples and explaining how these three common statistical methods work. Alhadad et al (2015), for Educause, have also produced a good summary.[12]

Hot topic: predicting the future

Predictive models are clearly very powerful and have the potential to assist significant positive change. However, it is important to note that they are often based on historic data, and changes in student demographics may have an impact on the validity of the model (West et al, 2016). Models need to be reviewed to ensure their accuracy is maintained. A predictive model, and actions taken as a result, may change the learning environment and

[12] https://library.educause.edu/~/media/files/library/2015/10/ewg1510-pdf (1.03MB)

remove some of the barriers that students would previously have faced. Likewise, analysis may indicate that elements of course material need to be redesigned or enhanced to assist learners. These may lead to more learners succeeding, which might require predictive models to be amended to account for these changes.

This is an emergent issue in the field, and there is not much literature available to investigate further at present. The main point to be made here is that predictive models need to be fit for their purpose and therefore subject to continuous review and revision.

Hot topic: data capability

If a key goal of learning analytics is to allow users of all kinds to be able to act appropriately and at the appropriate time to enhance the student experience, those users need to understand the data being presented to them.

Webb and Bailey (2018), reflecting on Jisc's experiences of developing a national learning analytics service, note that there is a desire for a better understanding of predictive models among the academic staff using them. However, they acknowledge that there are barriers to this understanding:

> 'The underlying assumption from most users was that model was based on rules, and it should show what factors led to a given prediction. The predictive model is actually based on logistic regression and neural networks and explaining to users from a non-mathematical background how this works is challenging.'

Webb and Bailey note that a work-around has been put in place that allows more detailed explanation for 'relatively numerate staff', along with a tool for other academic staff that uses a traffic light system to help explain how the prediction works.

Developing data capability is particularly challenging with respect to helping staff and students understand predictive models, but it is also required to work with wider data and learning analytics activity.

At the time of writing, The Open University is developing a Data Competency Framework and a Data Handbook that aims to increase data competency in staff. The Handbook is hosted on an internal SharePoint site and guides staff through the data used by the University, how it can be accessed, and some good practice pointers for data use. A key message is to ensure that staff are clear when specifying what data they need, and that data is defined and used consistently. The Open University's Quality Enhancement Unit has also produced a handbook to help Faculty staff use Analytics4Action tools to inform action planning in Boards of Studies (Rienties et al, 2016). QAA Scotland is also working with the sector as part of the Enhancement Theme to support the development of data capacity and capability in the sector.[13] This resource includes links to Open Educational Resources that offer training in various aspects of data capability, ranging from understanding and working with ways of presenting data to data modelling. This resource will be built on and developed.

Predictive analytics is a very technical subject: models are often comprised of multiple variables, subjected to complex statistical modelling. How can institutions best support their staff and students to better understand these models?

---

[13] www.enhancementthemes.ac.uk/current-enhancement-theme/sector-level-activity/optimising-the-use-of-existing-evidence

4. Using learning analytics to enhance the student experience

This section explores some of the ways in which learning analytics has been used to enhance the student experience. It explores two main areas: the use of learning analytics to support students at risk (interventions), and the use of learning analytics to improve curriculum and learning design.

Appendix A gives some examples of the use of learning analytics to enhance the student experience.

Interventions

The most common learning analytic tools used to direct interventions are predictive models and dashboards. These can help institutions identify students at risk, and then inform the development and deployment of interventions designed to help them improve their performance. Interventions can range from sending short messages reminding students to submit assignments to using machine learning technology to devise personalised learning pathways through a course of study.[14] Sclater (2017, p 115) lists several examples reproduced below:

- 'reminders sent to students about suggestion progression through the task
- questions to promote deeper investigation of the content
- invitations to take additional exercises or practice tests
- attempts to stimulate more equal contributions from participants in a discussion forum
- simple indicators such as red/yellow/green traffic signals, giving students an instant feel for how they are progressing
- prompts to visit further online support resources
- invitations to get in touch with a tutor to discuss progress
- supportive messages sent when good progress is being made
- arranging of special sessions to help students struggling with a particular topic'.

Good review

A Systematic Review of Learning Analytics Intervention Contributing to Student Success in Online Learning, Kew Si Na and Tasir (2017).

Interventions are designed to elicit a response in the student dependent on the purpose of the intervention, whether this is to submit an assignment, sign into the VLE and access particular learning activities, or seek support. In a review of 18 papers, Na and Tasir (2017) noted that interventions were concerned in the main with increasing engagement, addressing retention and increasing performance.

Sclater (2017) also notes that several factors may influence the effectiveness of interventions. These include:

- timing and frequency: it is important to consider when an intervention will be most effective and whether these will be repeated. Too often may result in students ignoring them, while positive feedback too soon may result in overconfidence.

[14] www.ontasklearning.org

- content: Sclater (2017) reports that the experience at Purdue indicated that students preferred personalised feedback even if the intervention itself was only a generic template that had been customised. Marist University implemented an incremental approach where the tone of the intervention would become more serious if the student did not respond or their performance had not improved (Jayaprakash, Moody, Lauría, & Regan, 2014).

Hot topic: evaluating interventions

There has been very little research work carried out to evaluate interventions, and the studies that have been carried out are inconclusive; see Sclater (2017), Whitmer et al (2017).

Ferguson and Clow (2017) examined issues around evidence that learning analytics improves learning by reflecting on the experiences gathered in evaluation work carried out in medicine and psychology. They used these experiences to illustrate some of the methodological and ethical lessons that learning analytics should seek to use or avoid during evaluation. These include:

- Although quasi-experimental techniques such as randomised control trials (RCTs) are thought to be the 'gold standard' in medical research and are commonly used in learning analytics evaluation, these can promote a 'simplistic view' that an intervention acts alone on a subject and in a context where all other variables are controlled. In other words, the intervention and nothing else causes any change in student behaviour (Pawson & Tilley (1997)).
- Correlation is not causation. Data can sometimes indicate that there may be a relationship between two variables (for example, an intervention of some kind and an uptick in student performance), but unless a causal link is identified between the two, one cannot be said to cause the other.
- For enhancement purposes, identifying what causes an improvement is as important as observing an improvement. For enhancement to adhere to its central definition - that is, the continuous improvement of the student experience - it is important to understand how the improvement has happened. This allows the relevant practice to be replicated, transferred to other contexts and further developed.
- Ethical issues may exist around withholding 'treatment' that may be beneficial to subjects in control groups: is it ethical to withhold a learning support tool to struggling students, even if its benefit is not known?
- Metrics and predictive models being used as proxies for student behaviour need to be robust, reliable and accurate.
- Publication bias (where evidence of impact is published, but the evidence to the contrary is not). Ferguson and Clow (2017) note in their analysis of the practice collected in the Learning Analytics Community Exchange (LACE) Hub that there was very little evidence that reported negative or no impact.

Ferguson and Clow (2017) emphasise that quantitative analysis alone will not suffice, and that analysis must consider the context in which the student is learning:

> 'Good quality quantitative research needs to be supported by good quality qualitative research: we cannot understand the data unless we understand the context.'

Dawson et al (2017) evaluated the effects of a predictive model with a large cohort of students (over 11,000) that was designed to detect students at risk of withdrawal and then offer interventions that aimed to improve their performance. Their evaluation showed that the interventions offered to students identified by the model did not have significant effect on retention. What makes this study particularly interesting is that preliminary statistical analysis showed a significant difference between students who received an intervention and those who did not, but that the difference (size effect) was very small. More sophisticated statistical analysis showed that there was no significant difference. The paper highlights several important points about evaluating interventions:

- the need for rigorous and robust statistical analysis, particularly in light of the constraints of the quasi-experimental methodologies mentioned above
- the need for more work to investigate the best methodologies to use when evaluating interventions that have been informed by learning analytics
- the need for predictive models to draw on information about individual 'differences such as motivation, employment, prior studies and self-efficacy' (in other words, the context in which students learn).

Evaluations of interventions will become more and more complex and difficult as institutions roll out learning analytics tools and increase the number of interventions that they inform. It may, for example, become difficult to evaluate whether a particular intervention has been effective, as it may have been implemented along with a plethora of other interventions and finding the causal relationship between intervention and effect might be difficult. This is particularly problematic for large institutions with large cohorts and complex support systems, which may issue multiple interventions from different sources. For these institutions, there is an added complexity: if interventions are not coordinated centrally, students may be inundated with interventions from different support systems within the institution, potentially reducing their effectiveness. It may be important for the institution to consider interventions from the students' point of view to ensure that this does not happen and to develop a holistic, institution-wide approach to interventions.

The Open University has attempted to address this issue in part by developing an Analytics4Action Evaluation framework (Rienties et al, 2016). It is described as a holistic framework for using and evaluating learning analytics which sought to include all stakeholders (but not students) as a core feature.

The framework identifies **six key steps**:

1. Key metrics and drill down: this involved bringing stakeholders together (staff involved directly with learning analytics; administrators; academics) in 'data touch point meetings' to look at all the data available from the University systems and ensure that all understood that data. The figure below reproduces which University data sources that were used:

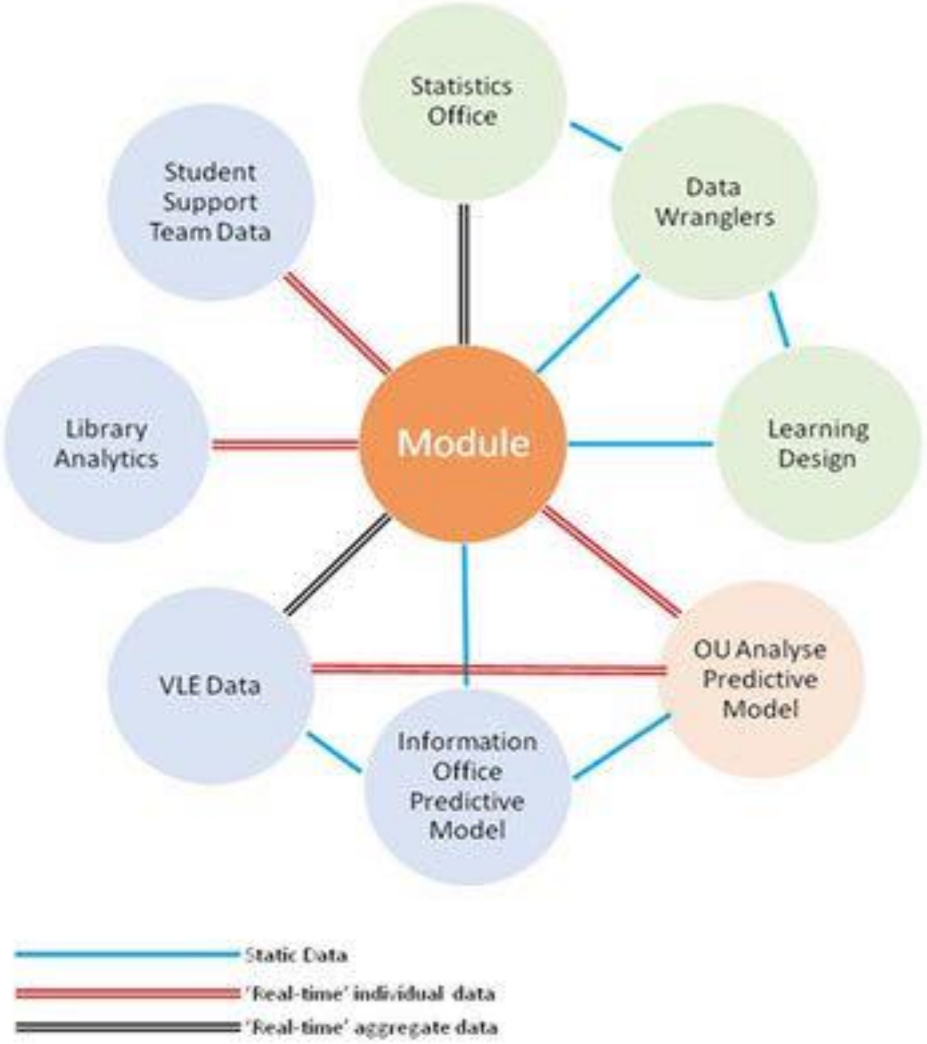


Figure 9: Data sources used in data touch point meetings (from Rienties et al, 2016)

2. Menu of response actions/interventions: academics are encouraged to consider a range of intervention/response options that are achievable within the institution. The menu is based on a Community of Inquiry model, articulated below. This attempted to define the teaching and learning context.

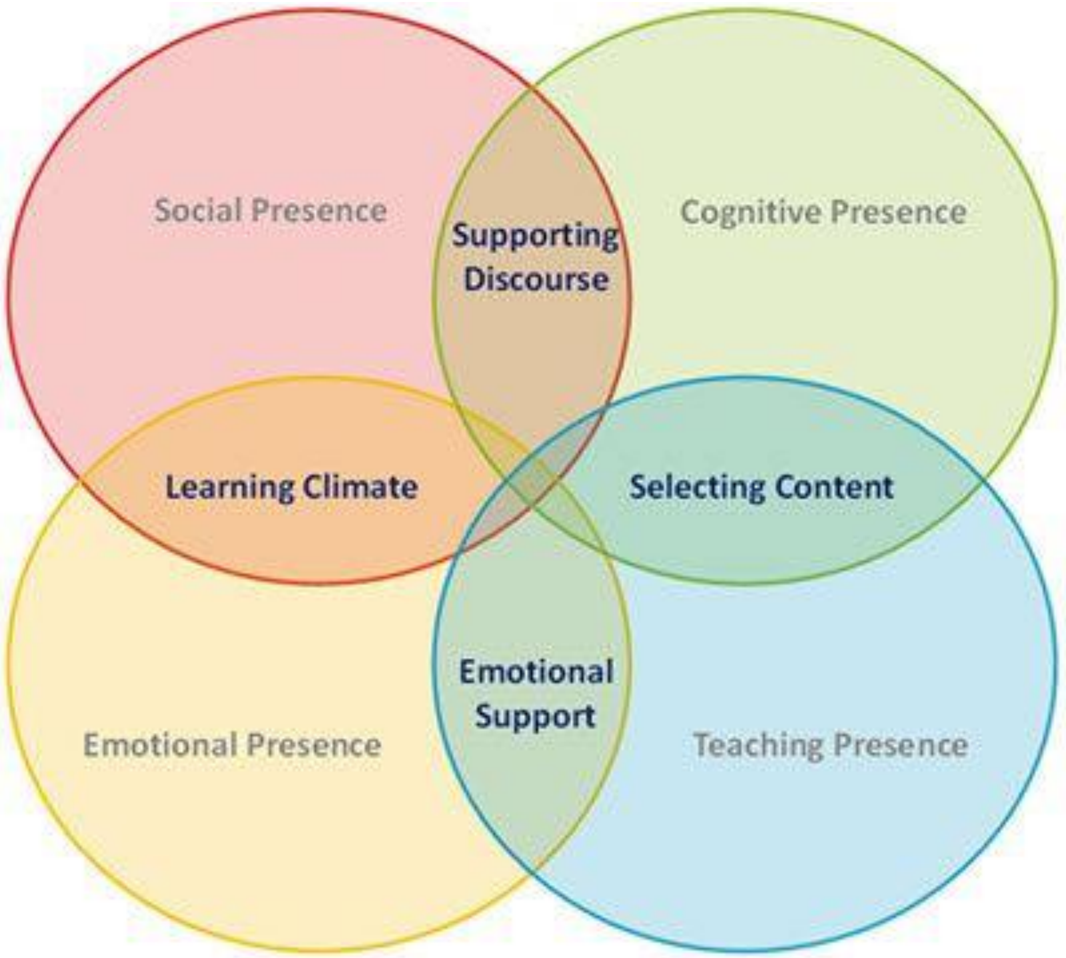


Figure 10: Community of Inquiry Model (from Rienties et al, 2016)

Figure 11, below, also maps particular interventions to each domain of presence articulated in the Community of Inquiry model.

Potential intervention options (learning design vs. in-action interventions).

	Learning design (before start)	In-action interventions (during module)
Cognitive Presence	* Redesign learning materials * Redesign assignments	* Audio feedback on assignments * Bootcamp before exam
Social Presence	* Introduce graded discussion forum activities * Group-based wiki assignment * Assign groups based upon learning analytics metrics	* Organise additional videoconference sessions * One-to-one conversations * Cafe forum contributions
Teaching Presence	* Introduce bi-weekly online videoconference sessions * Podcasts of key learning elements in the module * Screencasts of "how to survive the first two weeks"	* Organise additional videoconference sessions * Call/text/skype student-at-risk * Organise catch-up sessions on specific topics that students struggle with
Emotional Presence	* Emotional questionnaire to gauge students emotions * Introduce buddy system	* One-to-one conversations * Support emails when making progress

Figure 11: Potential intervention options (reproduced from Rienties et al, 2016)

3. Menu of protocols: this helps academics determine which research protocol will underpin the evaluation of the impact of the actions decided in step two. These include subjecting all students to the intervention, carrying out RCTs and pilot studies.

4. Outcome analysis and evaluation: evaluation of interventions is carried out using the research protocol identified in step three, although work is carried out in order to refine what variables will be affected by the intervention, and to control confounding factors. Effect size is also considered.

5. Institutional sharing of evidence: this is facilitated by sharing reports and outcomes on an Evidence Hub using a common template.

6. Deep dive analysis and strategic insight: regular meta-analysis of evidence base that might be able to help determine what works, why it works and when it works. This also allows the institution to examine whether existing metrics are fit for purpose and to change if necessary.

Other tools that have been developed to assist the evaluation of learning analytics interventions include the Learning Analytics Evaluation Framework developed by LACE.[15] This uses a series of Likert scale templates to determine users' experiences of using a learning analytics tool.

For the reasons articulated by Ferguson and Clow (2017), the effective evaluation of interventions arising from learning analytics still requires development. Major questions revolve around the ability of data to reflect learning behaviour. What can data from learning analytics tell us? What are the limits of the data's usefulness? How can qualitative data be usefully collected and utilised at scale to help determine what is happening? The field has attempted to address some of these questions by linking learning design and learning analytics (see below), but more work could be done to perhaps investigate how existing evaluation methodologies (such as social practice methods, realistic evaluations, and action theory) could be adapted and used with learning analytics.

Learning analytics and pedagogical approaches

When developing courses or learning materials, it is important to obtain evidence about how useful particular aspects of the course are to learners. Post-course evaluation and student representation have often been used as a source of evidence, but although they are vital mechanisms for capturing the student voice, they are reliant on the recollection of past events. Learning analytics can act as a source of useful data and evidence, its key strength being that it can provide this evidence in real time. Examining data produced by engagement with learning materials and activities can be the means of gaining detailed information about learners' immediate reactions to these and, subsequently, their learning behaviour within courses (Lockyer, Heathcote, & Dawson, 2013). Davies (2018) notes that a dashboard showing which areas of a course students are engaging with (and which they are not) may help direct lecturers' teaching activities and support, as well as influence design of future activities.

Additionally, course construction depends on the epistemological standpoints of those designing the course, whether these are conscious or unconscious, and this influences the pedagogical approach they use. Bakharia et al (2016) note: 'Much of this work (learning analytics)…is lacking in an understanding of the pedagogical context that influences student activities'. Linking these quite disparate fields of pedagogy (subjective, contested, debated

[15] www.laceproject.eu/evaluation-framework-for-la

and often deliberately ill-defined) and learning analytics (arguably objective, based on numerical data, algorithms and presented in a pseudo-scientific manner) is challenging. Several authors, including Lockyer et al (2013), Bakharia et al (2016) and Nguyen et al (2017) have suggested that the field of learning design provides a conceptual bridge between pedagogy and learning analytics:

> 'Essentially, learning design establishes the objectives and pedagogical plans, which can then be evaluated against the outcomes captured through learning analytics' (Lockyer, Heathcote, & Dawson, 2013).

As a field, learning design seeks to make explicit the thinking and processes that academics use when designing their courses (Hernández-Leo, Rodríguez-Triana, Salvador Inventado, & Mor, 2017). Mor and Craft (2012) define learning design as: 'the creative and deliberate act of devising new practices, plans of activity, resources and tools aimed at achieving particular educational aims in a given context'.

The Open University has carried out a substantial amount of work over the past decade investigating how student learning behaviours are stimulated by different learning designs, and rolling out learning design across module teams (Rienties, Nguyen, Holmes, & Reedy, 2017). The paper summarises much of the work the OU has carried out, including investigating VLE engagement and student performance, impact on student satisfaction and consideration of disciplinary adjustments. Four research areas were identified for future attention. These were:

- ensuring that learning design categories are appropriate, are used consistently by staff, and are both sufficiently precise and flexible
- determining which learning design activities will provide 'the optimum balance between student satisfaction and challenge in learning'
- surfacing the student perspective or voice in learning design
- identifying how learning analytics data collected in relation to learning design activities can be refined to surface 'fine grained learning behaviour'.

For more information about learning design

Lockyer et al (2013), Nguyen et al (2017).

Look out for: Bart Rienties and Quan Nguyen, The Open University, UK.

Hot topic: linking learning design and learning analytics

Hernández-Leo et al (2017), considering the connection between learning design and learning analytics, identify that there are promising possibilities for mutual support. Learning design, they note, may act as a translation device (through what they call 'a domain vocabulary'). This facilitates the use of learning analytics to examine pedagogical approaches. Conversely, learning analytics has the potential to provide robust and rigorous examination of the effectiveness of particular learning design. However, linking the two disciplines is still in its infancy. A framework is required to connect the two disciplines, and several have been suggested. These include:

- Checkpoint analytics (Lockyer, Heathcote, & Dawson, 2013)/temporal analytics (Bakharia et al, 2016): instructors analyse learners' use of key learning material at specific times, allowing them to ascertain if students are accessing these resources and progressing through the course as designers have planned. This analysis might draw on metrics such as time of access, duration of access, and unique page views.
- Process analytics (Lockyer, Heathcote, & Dawson, 2013): analysing how learners behave during specific learning activities that form part of an overall learning design, for example using social analytics to determine the pattern of engagement in a discussion-based learning task.
- Tool-specific analytics (Bakharia et al, 2016): analysis of data relating to specific learning tools, such as scores and attempts at a quiz, or the number of posts in a forum.
- Cohort dynamics (Bakharia et al, 2016): tracking individual learners' access to specific parts of the course, allowing the tracking of individual student progress through a course and the potential to relate this to performance, such as individual quiz scores, identifying individuals' access of particular tools or activities.
- Comparative (Bakharia et al, 2016): comparing aspects of the course, including differences in student participation for different learning activities; comparing engagement over different time periods (comparing behaviour across cohorts).

The Learning Analytics - Learning Design (LA-LD) Framework, developed by Gunn et al (2017), is another tool that is designed to help teachers to consider what data they require from learning analytics at different points in the teaching cycle: it seeks to anchor learning analytics data in real-life teaching practice.

Figure 12: Learning Analytics-Learning Design Framework

These frameworks illustrate the possibilities of how learning analytics could contribute to the design of learning materials and courses. There are still questions that need to be addressed. How can we ensure that the link between what is being designed and the desired student behaviour is known, understood and accurate? Conversely, how do we know that the learning analytics data being used accurately measures that behaviour? These are questions that, among others, the field is considering - but the debate should also involve other stakeholders, including students.

5. Implementing learning analytics in institutions

Universities are complex organisations, and the process of implementing any change can be difficult. Learning analytics is attempting to move from the domain of research findings to cross-institutional use, which is challenging not least because of the numbers and diversity of stakeholders involved (Ferguson et al, 2014). Most higher education institutions are at very early stages of adopting institutional approaches to learning analytics (Tsai, Moreno-Marcos, Tammets, Kollom, & Gasevic, 2018) - however, some frameworks and tools have been produced that aim to help institutions hold the right conversations and develop the right actions. These are provided below for information.

Ferguson et al (2014) offer a systematic approach that considers the many different factors that form part of attempting to implement learning analytics. This is based on the ROMA (Rapid Outcome Mapping Approach) model, which has been developed to offer an approach to implementation of other policy frameworks in complex environments.

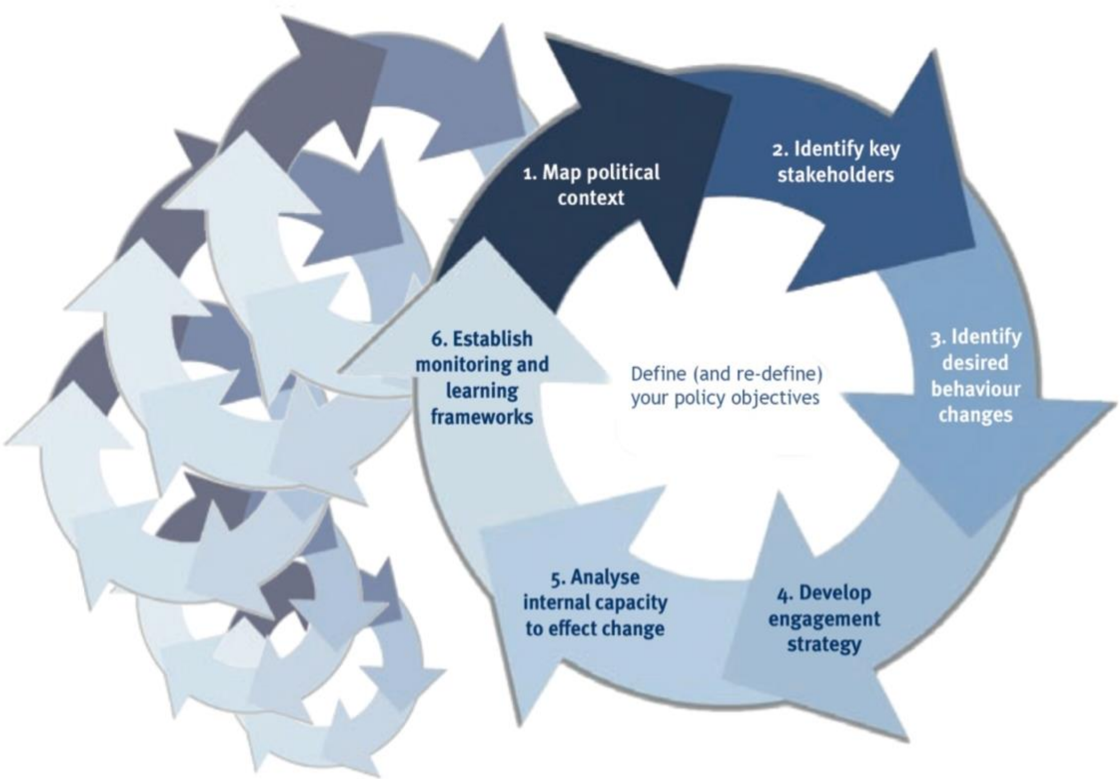


Figure 13: ROMA model

This model has been adopted by the SHEILA (Supporting Higher Education to Integrate Learning Analytics) project. The project (SHEILA, 2018[16]) has developed a framework that encourages institutions to consider the key issues of action, challenges and policy for each stage of the ROMA framework. This is represented diagrammatically below:

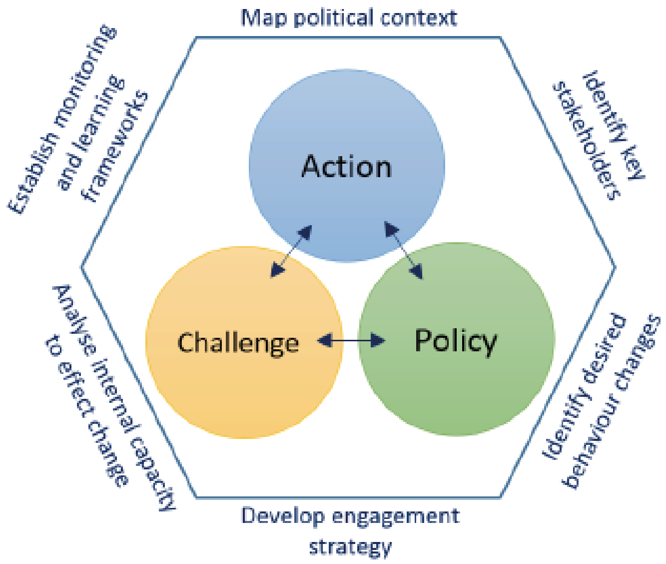


Figure 14: SHEILA policy framework structure (Reproduced from Tsai et al, 2018)

The SHEILA model is being adapted for use in Latin America through the LALA project involving institutions from Chile, Ecuador and institutions from Europe (Maldonado-Mahauad, Perez-Sanagustín, Kizilcec, Morales, & Munoz-Gama, 2018).

Ferguson and Clow (2017), reporting on a learning analytics expert workshop on the SHEILA project, identified many factors that would assist the successful implementation of learning analytics in an institution. These include:

1. A clear purpose for learning analytics, that is understood by everyone participating and is compatible with and supports existing organisational goals.
2. A sponsor from the senior management team to champion learning analytics, with a realistic understanding of what can be achieved. This was supported by a Murdock University case study (West et al, 2016) which reported that for learning analytics to be viable in an institution it needed sponsorship from senior managers.
3. A project leader to create realistic plans.
4. A project manager to take charge of day-to-day development.
5. Identification of accessible data sources.
6. Communicating the benefits to tutors and learners - this can take a sustained effort over time (West et al, 2016). Tutors and learners need to be able to appreciate the practical advantages of employing learning analytics (Gunn, McDonald, Donald, Milne, & Blumenstein, 2017).
7. The need to involve skilled data analysts who understand teaching and learning.
8. The need to train staff to handle the learning analytical outcomes (for example data literacy).

[16] http://sheilaproject.eu/wp-content/uploads/2018/08/SHEILA-framework_Version-2.pdf (124KB)

9 Consideration of the ethics of the development - including the learners' voice - in decision-making.

At the LAK18 conference, Hainey et al (2018) reported a case study where the ROMA model and the outputs of the SHEILA project were being used to map how the University of Strathclyde was implementing an institutional learning analytics approach. Activity planned was presented in a case study:

ROMA Stage	Definition	Institutional Direction/Method
Define policy objectives	Define objectives/motivations for learning analytics	• Enhance student learning experience
Map political context	Identify internal and external drivers	• Improve UK National Student Survey (NSS) results • Improve assessment & feedback and provide evidence for assessment & feedback policy • No retention issue at present however, there is recognition that expansion in distance learning and work based learning programmes could present a challenge • Institutional decision making
Identify key stakeholders	Identify users of learning analytics	• Students • Academics • Head of Departments/Director of Teaching • Vice Dean Academic/Faculty Dean • Senior Management Team • Professional Services • Institutional Education Committees
Identify desired behavior changes	Identify desired changes for key stakeholders in the current context	• Improved assessment experience and improve quality and timeliness of feedback for students • Provide academic staff with a mechanism to review their own assessment & feedback strategy

		• Provide evidence for course design and course review • Provide measurable data and evidence of success for senior departmental and faculty staff • Identify training opportunities for staff in assessment & feedback area • Improved student survey results and improved UK NSS scores in assessment & feedback
Develop engagement strategy	Scope areas related to ethics & privacy, financial & human resources, internal & external support, methodology, and stakeholder engagement	• Consult relevant policies and code of practice • Establish a Learning Analytics Board, with representatives from key stakeholders • Align learning analytics with other educational strategies, such as Learning Enhancement Framework • Conduct faculty and professional services collaboration sessions with staff and similarly with students to ensure positive engagement based on Agile Methodology • Continue with external engagement i.e. SoLAR, LAK, Jisc, SHEILA Project
Analyse internal capacity to effect change	Evaluate culture, legal frameworks, financial capacity, human capacity, and technological infrastructure	• Jisc Learning Analytics Readiness Assessment provided feedback on culture, processes, people and technology • Work with Information Governance Unit to ensure compliance with incoming General Data Protection Regulations • Creation of a data mart within the institutional data warehouse • Examine internal resource capabilities and seek to fund new appointments if needed
Establish monitoring and learning networks	Establish qualitative and quantitative measures of success	• Improved student satisfaction in student surveys • Increased student attainment • Operational efficiencies and satisfaction for academic staff • Increased NSS scores in assessment & feedback areas • Successful implementation of reviewed/revised assessment & feedback policy and associated staff training

Figure 15: University of Strathclyde use of ROMA

Jisc has also produced a questionnaire that institutions can use to assess their institutional readiness for learning analytics as part of their support for institutions.[17] Webb and Bailey (2018), reporting on the lessons learnt from the two-year Jisc programme to develop a national learning analytics service, identify a range of key points, many of which align with Ferguson and Clow's (2017) observations: in particular, the importance of key stakeholders and a user-centred approach. Webb and Bailey also make clear that progress and change needed time and to appreciate the 'legal and contractual complexity'. Data literacy is also highlighted as being important and reflected in one point regarding the wishes of data-users to understand predictive models.

[17] analytics.jiscinvolve.org/wp/on-boarding/step-6-readiness-assessment, accessed 18 October 2018.

6. Conclusion

This paper has attempted to summarise some of those emerging developments in the learning analytics research field that may be of interest to those institutional managers who are developing the use of learning analytics to enhance the student experience.

Much of the research activity focuses around learning analytics as used in a particular context and for a particular purpose. These pieces of work often involve other disciplines such as human-computer interaction, machine learning, mathematical modelling, statistics, use of pedagogical theories. The specialised nature of these disciplines means it can be difficult for someone who is not a specialist to engage with the work. It can be difficult for the institutional 'layperson'[18] to be able to understand and use the outputs from learning analytics activity, but there is demand for greater understanding among academic staff (Webb & Bailey, 2018).

For each hot topic articulated in this review, increasing the capacity for more institutional staff and students to engage with ethics, design, understanding and using learning analytics has emerged as an overarching trend. The learning analytics field recognises this: increased engagement with stakeholders was articulated as a major theme for the 2018 LAK conference. Finding ways in which to translate and use the outputs of research into application in institutions is challenging (Webb & Bailey, 2018); but if learning analytics is to be responsibly, accurately and ethically used within institutions, this translation and communication has to happen. If the definition of learning analytics articulated at the beginning of this review is used as a point of reference, learning analytics is only useful if it is used to enhance and understand student learning.

For learning analytics to reach its full potential, people who are directly involved in learning - whether as a learner or an educator - have to understand, to a certain extent, the research that underpins learning analytics. As Gunn et al (2017) state:

> 'If these gaps (between research and practice) are not addressed, learning analytics is likely to follow a well-established path from high expectations and exciting proof of concept results to another instance of technology that failed to make a significant impact on educational practice.'

Both teacher and student must trust that the data they are using is robust, ethically obtained and accurate to have confidence in using it. The more practitioners and students use learning analytics, the more testing and feedback data is available to those designing predictive models, dashboards and interventions. Gunn et al (2017) argue that teachers and students should not just be passive users of data, but involved in the design of learning analytic tools such as dashboards and predictive models. As Rienties et al (2017) note: 'put the power of learning analytics into the hands of teachers and administrators'.

Selwyn (2018) points out in his keynote for LAK 2018 that 'Learning analytics…have to start engaging with idiots like me': that is, the informed layperson. Democratising data - increasing the understanding and engagement of all stakeholders in learning analytics activity - is necessary not only to fully realise the potential of learning analytics, but to ensure that its potential is realised in an ethical manner. This could be partly achieved by holding the ethical debates, helping all stakeholders how to understand and use data, using participatory

---

[18] 'Institutional layperson' is used in this context to mean someone who has no specialised knowledge of learning analytics: for example, frontline teachers, institutional quality managers, and policy makers. The term does not encompass institutional staff who are researchers or who otherwise have expertise in learning analytics.

design techniques for dashboards and policy formation, and determining whether and how learning analytics activities actually help students.

There is one stakeholder voice that is still underrepresented in the literature, and that is students. The National Union of Students has produced a learning analytics guide for students' unions[19] and this emphasises the need for learning analytics to support the teaching and learning partnership. This means that students must be full partners in all the activities mentioned above. An obvious area to involve students in is the ethics debate. At least one institution (The University of Stirling) is encouraging its students to develop the institution's learning analytics ethical policy. Listening to, and capturing, the student voice must be a key objective of Scottish enhancement work in this area.

Finally, perhaps the most important challenge for institutions to address is to ensure that students are always seen as being more than just data points, as Paul Prinsloo reminds us.

‘You call me a misfit, a risk, a dropout and stop-out
Your research indicates that 'students like me' may not make it
You ask me questions regarding my financial status, where I live, how many dependents I have, and I know that once I tell you,
I will become a number on a spreadsheet
I will be color-coded
I will become part of a structural equation model that re-affirms that
People like me
Don't belong here
Somehow I don't fit in your spreadsheet
But I want you to know that I am so much more
I am so much more than how *you* define me
I am so much more than my home address
(the one I lied about to get access to funding or to get a place in residence)
I am also a brother, a sister, a mother, a dependent, a carer
I don't fit in your spreadsheets
I am not a dropout, I am a refugee, a migrant
I am in exile
Talk to me’

(Prinsloo, 2013)

[19] www.nusconnect.org.uk/resources/learning-analytics-a-guide-for-students-unions

Appendix A: Learning analytics case studies

Learning Analytical Focus	Learners	Analytics used	Institution	Comments
Signals Identifying at risk students early by using traffic light feedback to students with teachers sending messages to them to explain how at risk they are	Undergraduates	Performance, effort, prior academic history and student characteristics	Purdue University, Indiana, USA https://analytics.jiscinvolve.org/wp/files/2016/04/CASE-STUDY-A-Purdue-University.pdf (356KB)	Improvement in grades Majority of students said it was motivating Improvement in retention
Check my activity How to use information from considering use of VLE to make judgements of learners and what support to offer them Students given feedback on their use of VLE compared to other students	Undergraduates	Analysing the use of the VLE Based on simply the number of hits Poorer performing learners used VLE less	University of Maryland, Baltimore County, USA http://analytics.jiscinvolve.org/wp/files/2016/04/CASE-STUDY-B-University-of-Maryland-Baltimore-County.pdf (284KB)	Focus on the relationship between use of the VLE and performance Students who used Check my activity did achieve better outcomes than others However, better students may simply be using the VLE
At Risk Model - Staff Dashboard Attempting to develop a model to identify at risk students at enrolment	New undergraduates	Based on admission application, registration and placement test data, a student survey and financial information	New York Institute of Technology, USA http://analytics.jiscinvolve.org/wp/files/2016/04/CASE-STUDY-C-New-York-Institute-of-Technology.pdf (224KB)	The focus was improving retention and identifying at risk students as early as possible

Dashboard was provided to counselling staff, so they could judge whether to intervene or not				
Detailed analysis of learners' behaviour undertaking a course with integrated learning technology	Introduction to Comparative Religion course - undergraduates	Use of VLE Considering assessment, content engagement, administrative use	California State University, Chico, USA Research project concentrating on 377 students taking the course http://analytics.jiscinvolve.org/wp/files/2016/04/CASE-STUDY-D-California-State-University.pdf (364KB)	Findings showed: Important to clean data (eg remove staff postings) Overall use of VLE followed by assessment use best predictors Use of VLE better predictor than historic information
Open Source Tools	Undergraduates	This developed the Signals project to include gender and age, High School results and VLE uses (forum postings read and made as well as assessments) Models were developed with Marist data and then transferred to other institutions	Marist College, New York State, USA but later transferred to two community colleges and two universities with low retention rates http://analytics.jiscinvolve.org/wp/files/2016/04/CASE-STUDY-E-Marist-College.pdf (236KB)	Models have been released for others to develop and employ Models identified the majority of at risk students

Retention initiative Students identified were offered support by a central team	Non-traditional university students	Predictive model developed Reasons for drop out are complex and linked	Edith Cowan University, Perth, Australia [http://analytics.jiscinvolve.org/wp/files/2016/04/CASE-STUDY-F-Edith-Cowan-University.pdf (272KB)](http://analytics.jiscinvolve.org/wp/files/2016/04/CASE-STUDY-F-Edith-Cowan-University.pdf)	The analytical system for identifying at risk students needed to be supported with a system to aid learners 20% of students offered help took up the offer which is comparable with similar initiatives
A game designed to examine the ability of students to design a scientific investigation and produce a causal explanation	Middle school students	Student actions were identified plus demographic information and scores Two large pilots	Harvard Graduate School of Education, USA (Gibson & de Freitas, 2014)	Investigate patterns of behaviour and how they related to outcome Successful groups undertook specific actions so possibility of encouraging those actions to assist students join the most successful groups
Characteristics of dropping out and relationship between participation and final outcome from a MOOC	MOOC participants	Performance, survey, activity, grade and completion information	Curtin University, (Gibson & de Freitas, 2014)	Identify action patterns that might predict dropping out How participation in activities related to final outcome For participants who completed between 20

				and 69 out of 74 activities, a predictive link to outcome was discovered
To show the effectiveness of using low cost and open source learning analytical tools	One graduate course in occupational therapy	Information provided by Moodle VLE to spreadsheet, SNAPP and Voyant analysis	School of Occupational Therapy, USA, Western University Krusen, 2017	Analysis helped tutors consider the use of learning resources and each other
To improve student retention over a five-year period starting in 2015	Model applied at beginning of term and another applied during the term and the results compared to identify at risk students	Model based on regression analysis of five years of historic data Tested on last year cohort and showed 87% success rate	Brockenhurst College 16 to 19-year-old students Association for Learning Technology (2015)	Analysis allows for early proactive intervention replacing previous reactive tutor support Students are provided with visualisations of their information
Aim is to check that students are making reasonable progress using the predictive analysis	Predictive model allows for early assistance to be offered	Large scale use of a predictive model which is based on 10 years of data and 800 risk factors. 30,000 students being followed	Georgia State University (2015) www.youtube.com/watch?v=9Z-hp5NrSBg	Model trigger immediate intervention from an adviser. This has resulted cutting the mean time to achieve a degree, more students graduating and assisting disadvantaged students
Aim to build on earlier (pre-2014) efforts	Investigating Moodle analytical tools	Staff dashboard to identify at risk learners	Murdoch University, Australia	Central group founded in 2014 to

with the objective of improving retention	Explore options	Student dashboard	West et al, 2015	provide an institutional focus and bring together the different initiatives Senior management leadership and sponsorship
Aim is to use model to determine feedback and interventions	Predictive model	Analysis of student messages to assess their ability	Hong Kong Institute for Education Billy Tak Ming Wong (2017)	Polaris analytical tool
Aim is to consider how learners control their own learning	Student feedback on their social network activities	Analysis of third year undergraduates undertaking a blended learning course using e-portfolios and learner discussion in whole cohort and small groups. 72 students in total	University of Santiago de Compostela Baruiel et al (2016)	Comparison between previous year students and current ones plus questionnaires and Social Learning Network analysis

Appendix B: Learning analytics tools

This Appendix introduces some examples of tools to illustrate what is available, though it is beyond the scope of this paper to assess them. The Joint Research Centre Science for Policy Report (Ferguson et al, 2016) Annex 1 provides a list of tools across the schools, higher education, workplace and informal learning sectors. Each tool is explained. They reviewed 28 tools available across the educational sectors. These tools have a range of purposes such as predicting student achievement, general analysis of data and assessment. They use different forms of statistical analysis and output of the tools is presented using visualisations, summaries and descriptions.

SNAPP (Bakharia, Heathcote, & Dawson, 2009)

Social Networks Adapting Pedagogical Practice (SNAPP) is an open source tool that analyses the interaction of learners' forum communications. It provides visual representations of the communication between the participants. It aims to help tutors to manage forums and is based on the concept that effective student communication assists learning. It uses information drawn from Moodle or Blackboard VLEs.

GEPHI (Bastian, Heymann, & Jacomy, 2009)

GEPHI is an open source tool which offers visualisations of social networks. Hernandez-Garcia (2016) states that it has useful features for learning network analysis.[20]

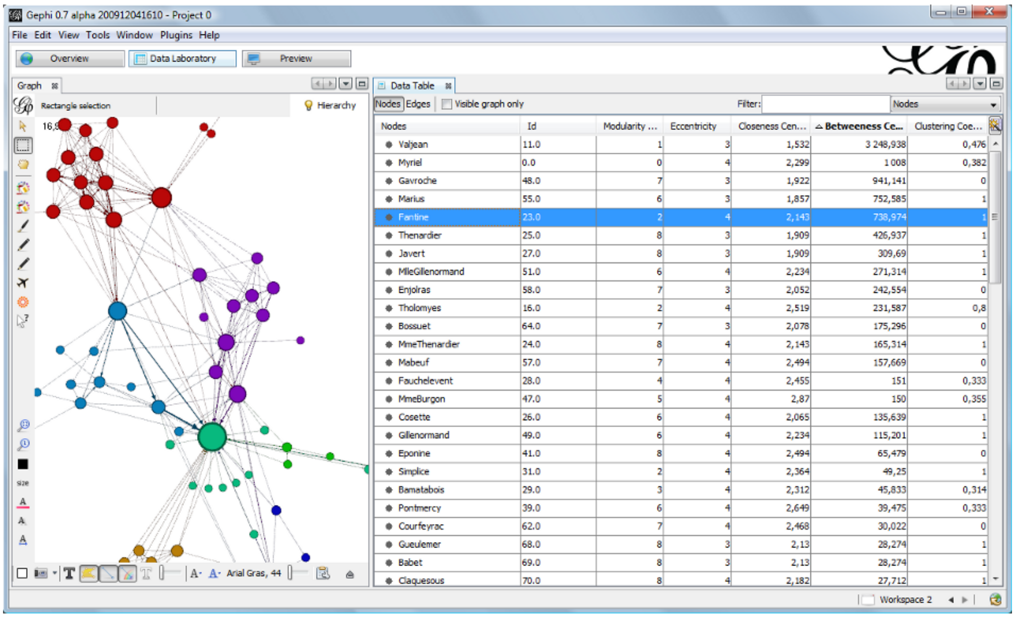


Figure 16: GEPHI Example (gephi.org/screenshots)

Voyant (Sinclair and Rockwell)

Voyant is a web-based set of tools to analyse digital texts. There are twenty-one different applications in the tool box to help you consider a digital text.[21]

[20] gephi.org

[21] docs.voyant-tools.org

OpenEssayist (Whitelock et al, 2015)

OpenEssayist is a real-time tool to help students analyse their academic essays to gain feedback that will help them reflect on and refine their writing.[22]

OU Analyse

OU Analyse is a project to use learning analytics to predict students at risk. You can request a demonstration of the tool by providing your email.[23]

Google Analytics

Google Analytics offers a range of information based on tracking users of your website or mobile app.[24]

Moodle Analytics

The Moodle VLE is widely used and comes with its own learning analytic tool including a model which predicts learner success. The model needs to be trained with your own data.[25]

Blackboard Analytics

Blackboard[26] is another widely used VLE which has a suite of learning analytical tools including tools to assist with learning design, prediction models of learner success and planning tools. Jisc also provides information on Blackboard services.[27]

Jisc

Jisc is working with a large group of universities and colleges to develop a learning analytics service for the post-16 and HE sector. The aim of the service is to offer organisations a full set of tools to track learners and an app to allow students to monitor themselves. The full service is scheduled to be available from August 2018.[28]

IADLearning

This is a commercial set of tools to work with the data from a VLE. It is intended to personalise learning and includes predictive elements.[29]

These are examples, and there are many others, but hopefully these will provide an indication of the possibilities.

---

22 www.open.ac.uk/researchprojects/safesea
23 analyse.kmi.open.ac.uk
24 support.google.com/analytics/answer/1012034
25 docs.moodle.org/34/en/Analytics#Predictions_processor
26 www.blackboard.com/education-analytics/index.html
27 https://analytics.jiscinvolve.org/wp/files/2015/10/Blackboard_Learning_Analytics_Discovery.pdf (68KB)
28 www.jisc.ac.uk/learning-analytics
29 www.iadlearning.com

Appendix C: Key organisations and journals

Name	Source	Notes
Society for Learning Analytics Research (SoLAR)	https://solaresearch.org/	An interdisciplinary network of leading international researchers who are exploring the role and impact of analytics on teaching, learning, training and development.
Journal of Learning Analytics Special Edition: Ethics and Privacy	https://solaresearch.org/%20stay-informed/journal/ Gasevic, D, Dawson, S and Jovanovic, J editors (2016), Special Edition Ethics and Privacy as enablers of learning analytics, Journal of Learning Analytics 3(1)	The journal is an official publication of the Society for Learning Analytics Research (SoLAR). With an international Editorial Board comprising leading scholars, it is the first journal dedicated to research into the challenges of collecting, analysing and reporting data with the specific intent to improve learning. 'Learning' is broadly defined across a range of contexts, including informal learning on the internet, formal academic study in institutions (primary/secondary/tertiary), and workplace learning.
Learning Analytics Community Exchange	www.laceproject.eu/	'The Learning Analytics Community Exchange was an EU-funded project in the 7th Framework Programme involving nine partners from across Europe…the project aimed to integrate communities working on LA and EDM from schools, workplace and universities by sharing effective solutions to real problems.'

Jisc	www.jisc.ac.uk/rd/projects/effective-learning-analytics	Jisc is a UK membership organisation which aims to support post-16 and higher education institutions with advice, research and services.
SHEILA (Supporting Higher Education to Integrate Learning Analytics)	http://sheilaproject.eu/	The SHEILA project will build a policy development framework that promotes formative assessment and personalised learning, by taking advantage of direct engagement of stakeholders in the development process.
Centre for the Study of College Student Retention	http://cscsr.org/	Based in USA to provide researchers and practitioners with a comprehensive resource for finding information on college student retention and attrition.
What Works? Student Retention and Success	www.heacademy.ac.uk/wasrs-programme/what-works-student-retention-and-success	The 'What Works?' programme sought to analyse and evaluate best practice skills to ensure high student retention in Higher Education Institutions (HEIs), with a focus on students from disadvantaged backgrounds. Twenty-two HEIs collaborating through seven distinct projects participated in the programme from 2008-11. The methodology consisted of combining student survey data, qualitative research with students and staff, literature reviews and analysis of institutional data.
Action on Access	http://actiononaccess.org/	A support and change-management partnership organisation - the national provider of coordination and support for furthering access, widening participation and increasing student retention and success and progression through higher education across the UK since 1999.
Learning Analytics in Australia	http://he-analytics.com/	'This site presents findings of an OLT-commissioned project (SP13-3249) that examined learning analytics uptake in the Australian higher education sector, its potential for retention, and identified affording and constraining factors mediating its uptake.'

Learning analytics: assisting universities with student retention	www.olt.gov.au/project-learning-analytics-assisting-universities-student-retention-2013	'Online learning platforms in conjunction with learning analytics software and student information systems can offer higher education providers with deeper, more meaningful and timely data with which to understand factors impacting student retention than has previously been possible. This provides opportunities for targeted interventions to address critical, time sensitive retention-related issues. This project will focus on the use of learning analytics to improve outcomes for students, particularly on retention and equity groups. The project will include two national surveys at an institutional and academic level to gather data on key infrastructure, the use of data and its application to improve teaching, learning and support to retain students. Survey data will be aligned with identified retention variables to develop a framework for critically reflecting on and providing guidance on how analytics can be used to retain students. Case studies from each of the partner institutions will be developed based on the application of the framework.'
Journal of Computer Information Systems	www.tandfonline.com/loi/ucis20	The Journal is a refereed (double blind) publication containing articles related to information systems and technology research.
International Journal of Computer Information Systems and Industrial Management Applications	www.mirlabs.org/ijcisim	'The IJCISIM is an international research journal, which publishes cutting edge research work from all areas of Computational Sciences and Technology.'
Journal of Educational Data Mining	www.educationaldatamining.org/JEDM/index.php/JEDM	This is an international and interdisciplinary forum of research on computational approaches for analysing electronic repositories of student data to answer educational questions. It is completely and permanently free and open-access to both authors and readers.

Bibliography

Alhadad, S, Arnold, K, Baron, J, Bayer, I, Brooks, C, Little, R, . . . and Whitmer, J (2015). *The Predictive Learning Analytics Revolution: Leveraging Learning Data for Student Success.* EDUCAUSE. Retrieved from https://library.educause.edu/resources/2015/10/the-predictive-learning-analytics-revolution-leveraging-learning-data-for-student-success.

Bakharia, A, Corrin, L, de Barba, P, Kennedy, G, Gasevic, D, Mulder, R, . . . Lockyer, L (2016). A conceptual framework linking learning design with learning analytics. *Sixth International Conference on Learning Analytics & Knowledge* (pp 329-38). New York: ACM.

Bakharia, A, Heathcote, E, & Dawson, S (2009). Social networks adapting pedagogical practice: SNAPP. *Same Places, Different Spaces, Proceedings ascilite 2009, 26th Annual ascilite International Conference.* Auckland: The University of Auckland, Auckland University of Technology, and Australasian Society for Computers in Learning in Tertiary Education (ascilite).

Bastian, M, Heymann, S, & Jacomy, M (2009). Gephi: an open source software for exploring and manipulating networks. *International AAAI Conference on Weblogs and Social Media.* AAAI.

Bennett, L (2018). *Challenges to the Design of Learning Dashboards.* Jisc.

Clow, D (2012). The learning analytics cycle: closing the loop effectively. *Second International Conference on Learning Analytics and Knowledge*, (p 134).

Davies, S (2018). *Data-informed blended learning design & delivery.* Jisc. Retrieved from https://www.jisc.ac.uk/events/student-experience-experts-group-meeting-25-apr-2018.

Dawson, S, Jovanovic, J, Gasevic, D, & Pardo, A (2017). From prediction to impact: evaluation of a learning analytics retention program. *Seventh International Learning Analytics & Knowledge Conference.*

Drachsler, H, & Greller, W (2016). Privacy and Analytics - it's a DELICATE issue. A Checklist for Trusted Learning Analytics. *Sixth Learning Analytics and Knowledge Conference.* Edinburgh.

Ferguson, R (2018). Future possibilities: analytics and enhancement. *Fifteenth enhancement in higher education conference: evaluation, evidence and enhancement: inspiring staff & students.* Glasgow: Quality Assurance Agency for Higher Education in Scotland.

Ferguson, R, & Clow, D (2017). Where is the evidence? A call to action for learning analytics. *LAK '17: Proceedings of the Seventh International Learning Analytics & Knowledge Conference* (pp 56-65). New York: ACM International Conference Proceeding Series.

Ferguson, R, Brasher, A, Clow, D, Cooper, A, Hillaire, G, Mittelmeier, J, & Vuorikari, R (2016). Research evidence on the use of learning analytics - implications for education policy. In J Vuorikari & J Castaño Muñoz, *Joint Research Centre Science for Policy Report.*

Ferguson, R, Hoel, T, Scheffel, M, & Drachsler, H (2016). Guest Editorial: Ethics and Privacy. *Journal of Learning Analytics, 3*(1).

Ferguson, R, Macfadyen, L, Clow, D, Tynan, B, Alexander, S, & Dawson, S (2014). Setting Learning Analytics in Context: Overcoming the Barriers to Large Scale Adoption. *Journal of Learning Analytics, 1*(3), 120-144.

Gasevic, D, Dawson, S, & Jovanovic, J (2016). Ethics and Privacy as Enablers of Learning Analytics. *Journal of Learning Analytics*(28), 1-4.

Gibson, D, & de Freitas, S (2014). Exploratory learning analytics methods from three case studies. *Rhetoric and Reality: Critical perspectives on educational technology* (pp 383-88). Dunedin: ascilite.

Gilmour, A, Boroowa, A, & Herodotou, C (2018). *Using predictive analytics to support students.* Quality Assurance Agency for Higher Education in Scotland.

Gunn, C, McDonald, J, Donald, C, Milne, J, & Blumenstein, M (2017). *Building an evidence base for teaching and learning design using learning analytics.* Wellington: Ako Aotearoa - The National Centre for Tertiary Teaching Excellence.

Hainey, A, Green, B, Thornbury-Gould, H, Ramsay, H, & Milligan, C (2018). Developing an Institutional Policy using the RAPID Outcome Monitoring Approach. *Eighth International Learning Analytics and Knowledge Conference.*

Hernández-Leo, D, Rodríguez-Triana, M, Salvador Inventado, P, & Mor, Y (2017). Connecting Learning Design and Learning Analytics. *Interaction Design and Architecture(s) Journal*(33), 3-8.

Jayaprakash, S, Moody, E, Lauría, E, & Regan, J (2014). Early alert of academically at risk students: an open source analytics initiative. *Journal of Learning Analytics, 1*(1), 6-47.

Jivet, I (2018). Adaptive learning analytics dashboard for self-regulated learning. *8th Conference of Learning Analytics and Knowledge (LAK18).*

Jivet, I, Scheffel, M, Drachsler, H, & Specht, M (2017). Awareness Is Not Enough: Pitfalls of Learning Analytics Dashboards in the Educational Practice. *Data Driven Approaches in Digital Education*, (pp 82-96).

Knight, D B, Brozina, C, Stauffer, E, Frisina, C, & Abel, T (2015). Developing a learning analytics dashboard for undergraduate engineering using participatory design. *ASEE Annual Conference and Exposition.* Seattle, WA: American Society for Engineering Education.

Lockyer, L, Heathcote, E, & Dawson, S (2013). Informing pedagogical action: aligning learning analytics with learning design. *American Behavioral Scientist, 57*(10), 1439-59.

Maldonado-Mahauad, J, Perez-Sanagustín, M, Kizilcec, R, Morales, N, & Muñoz-Gama, J (2018). Mining theory-based patterns from Big data: Identifying self-regulated learning strategies in Massive Open Online Courses. *Computers in Human Behavior*(80), 179-96.

Mor, Y, & Craft, B (2012). Learning design: reflections on a snapshot of the current landscape. *Research in Learning Technology, 20*.

Na, K S, & Tasir, Z (2017). A Systematic Review of Learning Analytics Intervention Contributing to Student Success in Online Learning. *International Conference on Learning and Teaching in Computing and Engineering* (pp 62-68). Hong Kong: LaTiCE.

Nguyen, Q, Rienties, B, & Toetenel, L (2017). Mixing and Matching Learning Design and Learning Analytics. *Learning and Collaboration Technologies: Technology in Education - Fourth International Conference, LCT 2017 held as Part of HCI International 2017* (pp 302-16). Vancouver: Springer.

Pawson, R, & Tilley, N (1997). *Realistic Evaluation.* Sage.

Prinsloo, P (2013). Using student data: Moving beyond data and privacy protection to student data sovereignty as basis for an ethics of care. *13th International Conference on E-Learning (ICEL).* Cape Town: Cape Peninsula University of Technology (CPUT).

Prinsloo, P, & Slade, S (2016). Student vulnerability, agency, and learning analytics: an exploration. *Journal of Learning Analytics, 3*(1), 159-82.

Rienties, B, Boroowa, A, Cross, S, Kubiak, C, Mayles, K, & Murphy, S (2016). Analytics4Action Evaluation Framework: A Review of Evidence-Based Learning Analytics Interventions at the Open University UK. *Journal of Interactive Media in Education,1*(2), 1011.

Rienties, B, Nguyen, Q, Holmes, W, & Reedy, K (2017). A review of ten years of implementation and research in aligning learning design with learning analytics at the Open University. *Interaction Design and Architecture(s)*(33), 134-54.

Schwendimann, B A, Rodriguez-Triana, M J, Vozniuk, A P, Boroujeni, M S, Holzer, A, Gillet, D, & Dillenbourg, P (2017). Perceiving Learning at a Glance: A Systematic Literature Review of Learning Dashboard Research. *IEEE Transactions on Learning Technologies, 10*(1), 30-41.

Sclater, N (2016). Developing a Code of Practice for Learning Analytics. *Journal of Learning Analytics, 3*(1), 16-42.

Sclater, N (2017). *Learning Analytics Explained.* New York: Routledge.

Sclater, N, & Mullan, J (2017). *Learning analytics and student success - assessing the evidence.* Jisc.

Sclater, N, Peasgood, A, & Mullan, J (2016). *Learning analytics in higher education: a review of UK and international practice.* Jisc.

Selwyn, N (2018). The Promises and Problems of Learning Analytics. *Eighth International Learning Analytics and Knowledge Conference.*

Slade, S, & Prinsloo, P (2013). Learning analytics: ethical issues and dilemmas. *American Behavioral Scientist, 57*(10), 1509-28.

Tsai, Y-S, Moreno-Marcos, P M, Tammets, K, Kollom, K, & Gasevic, D (2018). SHEILA policy framework: Informing institutional strategies and policy processes of learning analytics. *8th International Conference on Learning Analytics and Knowledge* (pp 320-29). New York: ACM Press.

Viberg, O, Hatakka, M, Bälter, O, & Mavroudi, A (2018). The Current Landscape of Learning Analytics in Higher Education. *Computers in Human Behavior*.

Vozniuk, A, Govaerts, S, & Gillet, D (2013). Towards portable learning analytics dashboards. *EPFL Switzerland.* Beijing: ICALT.

Webb, M, & Bailey, P (2018). Scaling Nationally: Seven Lessons Learned from Jisc's National Learning Analytics service. *Eighth International Learning Analytics and Knowledge Conference.*

West, D, Huijser, H, Heath, D, Lizzio, A, Tooley, D, Miles, C, . . . Bronniman, J (2016). Higher education teachers' experiences with learning analytics in relation to student retention. *Australasian Journal of Educational Technology, 32*(5).

Whitmer, J, Nasiatka, D, & Harfield, T (2017). *Student interest & patterns in learning analytics notifications.* Blackboard.

Wong, B T (2017). Learning analytics in higher education: an analysis of case studies. *Asian Association of Open Universities Journal, 12*(1), 21-40.

Please note that all web links in this document were accessed on 27 November 2018.

18 Bothwell Street, Glasgow G2 6NU
Registered charity numbers 1062746 and SC037786

Tel: 0141 572 3420
Web: www.enhancementthemes.ac.uk