Learning analytics: a firm basis for the future

Book Section

Learning analytics: a firm basis for the future

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Abstract

Learning analytics take the data we leave behind us as we engage with education and use those data to improve teaching and learning. Today, those data are mainly gathered from virtual learning environments. In the future they are likely to include personal and environmental data collected by sensors that we wear or that are embedded in the objects around us. This chapter draws on two international studies to examine the possibilities offered by learning analytics, and the challenges they offer. It provides a set of key questions to ask when developing, implementing or making use of analytics.

Introduction

Learning analytics is a fast-developing field of research that has emerged since 2011 and has been taken up worldwide, especially in Europe, North America and Australia. The field has its roots in data mining and in business intelligence. It also makes use of methodologies and theories developed in disciplines as diverse as artificial intelligence, computer science, education, learning sciences, linguistics, machine learning, philosophy, psychology, sociology and statistics (Dawson *et al.* 2014).

The Society for Learning Analytics Research (SoLAR) defines learning analytics as ‘the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs’ (Siemens *et al.* 2011, p4). Although much early work has focused on the data processing and analysis that make up the first half of this definition, the aim is to provide actionable insights that can make a practical difference to education. In the future, analytics could be used to tackle big problems such as gender and diversity issues, youth mobility, inclusion, and drop out from education.

Learning analytics has recently emerged as a field in its own right, distinct from other work on technology-enhanced learning and broader work on analytics. This has been attributed to three principal drivers, big data, online learning and national concerns (Ferguson 2012):

1. **Big data:** the widespread adoption of institutional databases and virtual learning environments (VLEs) means that schools and universities now generate increasingly large amounts of data, and want to make use of these assets to improve learning and teaching.

2. **Online learning:** This increase in available data has been paralleled by an increase in take-up of online and blended teaching and learning. At the same time, more and more learners are learning informally using open educational resources (OERs) and massive open online courses (MOOCs). There is therefore growing international interest in how to optimise learning in these settings.

3. **National concerns:** Countries and international groupings are now more able to compare statistics related to schooling. Well-known examples of systematic evidence gathering that enable such comparisons include the Programme for International Student Assessment (PISA) and the Trends in International Maths and Science Survey (TIMMS). As a result, countries are increasingly interested in measuring, demonstrating and improving performance in education and are looking for ways to raise educational standards in order to benefit their citizens and society as a whole.

As well as these drivers, the field also faces a variety of challenges. These include the rapid pace of change in technology-enhanced learning, the problems associated with implementing analytics within an educational institution, and confusion about what learning analytics are and what they can do.

As learning analytics are an example of technology-enhanced learning, they must respond to a rapid rate of change. ‘Typically, we find that the doubling time for different measures – price-performance, bandwidth, capacity – of the capability of information technology is about one year' (Kurzweil 2005, p56). This fast pace of change means that if, in 2006, developers had begun to implement learning analytics without looking ahead, they would not have been able to plan for learning with and through social networks (Twitter registered its first members in July 2006), learning with smartphones (the first iPhones went on sale in 2007), or learning at scale (the term MOOC was introduced in 2008). Analytics take time to develop, so this work needs to be carried out with an eye to the future in which they will be implemented, rather than in relation to technology that will soon be outdated.

Analytics in 2016 draw on data from virtual learning environments, also known as learning management systems (LMS). However, these systems are not the only source of data. Already furniture, pens, writing pads – almost any tool used during learning – can be fitted with sensors. These can record many sorts of information, including tilt, force and position. Video cameras using facial recognition are able to track individuals as they learn in lecture theatres or online. These cameras monitor movements, and can record exactly how learners work with and manipulate objects, as well as where they focus their gaze. In addition, sensors can be used to gather personal information about factors such as posture, attention, rest, stress, blood sugar, and metabolic rate. In future, learning analytics could draw on combinations of these data sources in order to enhance teaching and learning.

Although technology changes quickly, educational institutions do not. They function as complex adaptive systems (Ferguson *et al.* 2015). That is to say, they exist as dynamic networks of interactions, made up of nested and clustered sets of similar subsystems. This means that educational institutions can prove extremely resistant to change. Changes that target only their subsystems are unlikely to succeed. Even when the focus is at institutional level, learning analytics and other insights based on data may not be put into practice for many reasons. These reasons include a tendency to make decisions based on anecdote rather than on research, a focus on technical concerns, a failure to incorporate analytics within a process of evidence-based decision making, and the often low levels of management familiarity with statistical methods and analytics (McIntosh 1979, Macfadyen and Dawson 2012).

Together, these factors mean that when educational institutions consider learning analytics, they often look for the ‘low-hanging fruit’ – data that are easy to gather and systems that are straightforward to implement. However, many tools that appear to offer these straightforward learning analytics solutions do little more than present a series of data visualisations. Although these make use of large sets of educational data, they are not necessarily ‘actionable’ in the way that learning analytics should be. They do not make it clear what actions should be taken in order to improve learning or teaching, they may distract attention from more immediate issues, and they sometimes prove to be nothing more than an expensive way of telling teachers things that they already know.

In order to address these challenges and, in particular, to help to deal with the rapid rate of technological change that influences the development of the field, two international studies have examined the current state of learning analytics and looked at what the future holds in store.

The first of these was the Visions of the Future study, run by the Learning Analytics Community Exchange (LACE) project (Griffiths *et al.* 2016b). This was a Policy Delphi study (Turoff 2002) that systematically solicited and collated informed judgments on learning analytics from experts and used these to identify the areas that these experts judged most important to the successful implementation of learning analytics in the next ten years. In order to do this, the study used eight 'visions of the future of learning analytics' as provocations that would prompt reflection and thoughtful responses (Ferguson *et al.* 2016b).

Examples of the visions used as provocations in the Policy Delphi study

In 2025, classrooms monitor the physical environment to support learning and teaching

In 2015, learning analytics were mainly used to support online learning. By 2025, they can be used to support most teaching and learning activities, wherever these take place. Furniture, pens, writing pads – almost any tool used during learning – can be fitted with sensors. These can record many sorts of information, including tilt, force and position. Video cameras using facial recognition are able to track individuals as they learn. These cameras monitor movements, and record exactly how learners work with and manipulate objects. All this information is used to monitor learners' progress. Individuals are supported in learning a wide range of physical skills. Teachers are alerted to signs of individual learner's boredom, confusion, and deviation from task. Teachers and managers are able to monitor social interactions, and to identify where they should nurture socialisation and cooperative behaviour.

In 2025, individuals control their own data

In 2015, it was not clear who owned educational data, and it was often used without learners' knowledge. By 2025, most people are aware of the importance and value of their data. Learners control the type and quantity of personal data that they share, and with whom they share it. This includes information about progress, attendance and exam results, as well as data collected by cameras and sensors. Learners can choose to limit the time for which access is allowed, or they can restrict access to specific organisations and individuals. The tools for making these choices are clearly laid out and easy to use. In the case of children, data decisions are made in consultation with parents or carers. If they do not engage with these tools, then no data is shared and no benefits gained. Most educational institutions recognise this as a potential problem, and run campaigns to raise awareness of the both the risks of thoughtless exposure of data, and the benefits to learners of informed sharing of selected educational data.

The second study focused on the implications of learning analytics for educational policy (LAEP). It based its findings on state-of-the-art reviews of the literature, tools, policies and practices, on case studies, and on focus group work with international experts (Ferguson *et al.* 2016a).

Together, these two studies revealed how learning analytics were being used and developed in 2016, and highlighted areas that would need attention in the future. At a national scale, these two studies showed how governments could influence the development of learning analytics. At a local scale, they pointed to five questions that institutions and individuals need to answer if they plan to implement learning analytics (Table 1).

Table 1: Analytics implementation checklist

1	What do we want to achieve?
2	How will our analytics improve learning?
3	Where is the evidence?
4	Do staff and learners know how to use the analytics?

5	Who is in control and how is this regulated?

The following sections look at each of the areas on this checklist in turn, explaining what these questions imply and why they are important. These sections include quotes from participants in the LACE Visions of the Future study (VoF). The study had 133 participants from 21 countries. Participants included invited experts drawn from different sectors of education (schools, higher education and workplace learning) as well as volunteers who responded to publicity about the survey, all of which was targeted at learning analytics researchers, developers and practitioners. Within this chapter, four-digit numbers (for example, 2804) are used to identify individual respondents. The quotes are used verbatim, although capitalization has occasionally been changed to align with sentence structure.

What do we want to achieve?

As one VoF respondent phrased it, ‘It all starts with the pedagogical perspective’ (2804) – that is, with a theorized approach to teaching and learning. If analytics are to support these activities then it is important to know why we are engaging in them and what we want to achieve. We also need to examine our basic assumptions about knowledge, including whether it is stable or changing, whether it is made up of discrete facts or interrelated concepts, whether it exists outside the self and can be transmitted or is constructed by the self (Knight *et al.* 2014).

Many VoF respondents linked their view of learning analytics to their understanding of what education is for. They associated education with change, growth, transformation and the development of society. Respondent 3462 believed that ‘We have a social duty to facilitate and provide opportunities for learners to achieve their full potential’, while 6064 felt that ‘Education overcomes historical injustices’.

Such views suggest that, in future, we shall need to move beyond the present focus on the use of learning analytics to reduce course drop-out rates or to improve performance in certain subjects. Georgia State University in the USA, for example, is already using analytics to eliminate achievement gaps based on race, ethnicity and economics (Georgia State University 2015) while University of Technology Sydney (UTS) is using them to support the development of 21st-century skills and competences that underpin lifelong learning (Ferguson *et al.* 2016a).

For example, a major research project at UTS uses various technologies to carry out automated analysis of student writing, in order to provide formative feedback on essay drafts. Another project at the same university makes use of the CLARA self-assessment survey tool. CLARA was developed to make students aware of the habits of mind they bring to their learning (their ‘learning dispositions’). The tool generates visualisations for each student that represent their current ‘learning power’. It also suggests interventions that are based on those learning profiles. These automated visualisations and suggestions are used to support coaching and mentoring of students by trained peers and by staff.

As well as considering the purposes of education, VoF respondents also made explicit what they meant by learning: ‘an essentially social activity which relies on mutual trust and confidence’ (0649), ‘a human, socially embedded, communal activity’ (7473). Respondent 5297 picked out the types of activity involved in learning: ‘Education is about collaboration, about human interaction, about creativity, about innovation and about spontaneity’ (5297). Together, these comments drew attention to the human and social elements of the learning process.

An idea expressed by many was that human interaction is a crucial part of the learning process – ‘we need a human teacher to guide and scaffold us’ (6818). These respondents stressed that analytics cannot be understood without interpretation that makes reference to their context. Humans, specifically teachers, are needed to make sense of analytic output and to make use of it to support learning.

Social definitions of learning also made the point that focusing only on the data produced by individuals produces an impoverished picture of their learning. Analytics need to be able to provide feedback on how people construct knowledge together, as the SNAPP tool does when it analyses the social networks in online learning groups (Bakharia and Dawson 2011). Work on social learning analytics and discourse analytics is already exploring these possibilities (Buckingham Shum and Ferguson 2012, McNamara *et al.* 2014).

Some respondents worried that learning analytics could be used to remove essential but challenging elements of the learning process. ‘Learning is not only about success is about learning from failure’ (3614); ‘there is a time for learners to be confronted in order for transformation and growth to occur’ (3462). Sometimes ambiguity, conflict and uncertainty are elements that prompt the construction of knowledge. A potential danger of personalised learning is that it does not present learners with the most difficult problems and a discipline’s overarching challenges. If a system automatically adjusts its difficulty level so that learners are always working within their comfort zone, then they may never be asked to deal with and benefit from challenge.

Overall, respondents were ambitious with regard to what learning analytics may be able to achieve in the future. Their visions did not focus simply on institutional concerns such as increasing retention and improving grades. Instead, they presented a wider view of the role of education. Education was seen as a route to individual transformation and the development of society, a way of developing skills and competencies for every stage of life, and of reducing the impact of demographic and economic inequalities. Respondents also stressed the need to take into account pedagogic perspectives that emphasise the importance of interaction and communication to the construction of knowledge.

How will our analytics improve learning?

It is clearly difficult to express a dynamic process of transformation, innovation and spontaneity in terms of measurable items. Some VoF respondents felt that learning is not open to observation in this way and that it is difficult to define success in measurable terms that hold true in different contexts. Others felt that it is dangerous to equate learning with measurable outcomes because this would ‘reduce learning to the acquisition of those skills that can be measured and advised by the sensors and apps’ (8698). However, others referred to existing or ongoing research that shows relationships between activities and progress towards learning goals or changes in learning behaviour (see, for example, Pistilli *et al.* 2012, Rienties and Toetenel 2016).

Unless it becomes possible to measure changes to the human body that reliably indicate learning is taking place, analytics will continue to rely on proxies for learning such as performance on tests before and after a period of learning. Respondent 6446 suggested that ‘work should focus on understanding how the learning process really works’, developing a nuanced model that applies to individual learners rather than to learners in general. Respondent 4762 proposed the development of a new proxy for learning – ‘correlation between what somebody learns and the visual perception of how s/he is learning’. Others observed that learning does not take place only in the classroom, so learning analytics cannot only be designed for closely controlled environments but need to take into account the wider experience of learners.

This wide range of possible learning contexts means that ‘it demands enormous quantity of data to monitor individual learning’ (2428). However, many respondents were optimistic that data problems can be dealt with, pointing to existing work and experience. As respondent 0649 noted, it is ‘hard to believe that there will be enough processing power to do this, but I guess people always say that when something is ten years away’.

Smart houses, wearable technology, the Internet of Things (a network of devices that can collect and exchange data) and face recognition are increasingly familiar parts of everyday life, so the data collection and data-crunching necessary for learning analytics should not prove to be impossible and may be closer that ‘ten years away’. ‘There exist already tools that monitor what is happening in blended learning scenarios and provide teachers -and learners- advice, in different ways’ (8698). However, data collection and data crunching alone do not necessarily improve learning, so choosing a set of proxies for learning and collecting information about them is only part of the challenge.

The question ‘How will our analytics improve learning?’ therefore leads to a much broader question – ‘What does it mean to improve learning?’ We are so used to seeing improvement represented in terms of test results and examination performance that it is easy to forget that these are only proxies that help us to assess the effects of complex processes of cognitive and social change. New ways of collecting and processing data may open up new ways of identifying and supporting learning gains. As we make progress with the development of learning analytics, we also need to develop our understanding of what it means to learn.

Where is the evidence?

The complexity of the problem means that learning analytics solutions must often make a range of assumptions about which combinations of data provide evidence that learning has, or has not, taken place in a certain context. It is difficult to interrogate these assumptions if there is a ‘black-box’ situation in which data are input and results generated without users receiving any information about the intervening process. Even when the underlying algorithms are open to scrutiny, users may not have the time or the expertise to check them, or to recheck them when conditions change.

This is dangerous, because it is then difficult to check that the results are reliable (similar data always produce similar results), valid (the results are meaningful) and generalizable (the same analytics will be valid in a variety of contexts). Without a robust quality assurance process in place, users will find it difficult to judge the value of any analytics solution.

Validating analytics will involve linking behaviours and measurable outcomes clearly with pedagogy and with learning benefits, as well as employing an appropriate and robust scientific method. ‘The use of LA applications in real practice has be conscious of the limitations of any analysis, and apply them in a way that is coherent with the limitations of the approach' (8698). Validating analytics will also mean selecting and representing data carefully, using an appropriate conceptual framework and taking context into account when reporting results.

> *Research in this space should be tied to pedagogical outcomes. If certain monitoring provides tangible learning benefits, than it should be explored further. If we are just collecting data because we can, and then trying to fit it to arbitrary behavioural outcomes, then the work is futile.* (2625)

Validation will also need to build on previous work in learning analytics and in related fields, and will involve scientific co-operation and discussion to share and build on results. Overall, the research should build into a reliable evidence base. Reviewers will need to ensure there is no hype or misrepresentation of results, and that no conflict of interest is involved. They also need to examine underlying assumptions. If, for example, an algorithm is developed to recommend future qualification paths and career paths based on data from previous students, it could perpetuate inequalities if it fails to take into account past discrimination that has limited the success of particular groups.

Even once the quality assurance process is in place, educators and learners will need training in order to be able to question the analytic process and its assumptions, to avoid analytics that have not been validated, and to make use of analytics in an appropriate way. ‘Lots of professional learning would be required to ensure that all this information is interpreted and used appropriately’ (4352).

‘Where is the evidence?’ is a question we need to keep in mind whenever analytics are in use. In many areas of our life, technology has become so complex that it can only be understood or fixed by trained experts. There is a real danger that learning analytics could follow the same route, using processes and algorithms that are incomprehensible to most teachers and learners. It will be important to develop processes at national and local levels to ensure that learners and teachers are involved with the development and validation of the analytics that influence their lives.

Do staff and learners know how to use the analytics?

Embedding analytics effectively within teaching practice will mean that analytics need to be covered in initial educator training, and within continuing professional development. This training will enable educators to make use of these new tools, to interpret the additional information appropriately and to use the data in meaningful ways.

Staff need to be aware of what analytics can and cannot do, and they need to be able to challenge overblown claims with confidence. They also need opportunities to engage in discussion about the goals and purposes of learning analytics.

A national report on learning analytics in Australia identified capacity building as an issue across the country, and suggested that this capacity building would require not only programmes of professional development, but also academic courses and secondment opportunities (Colvin *et al.* 2015). This training would be designed for classroom teachers and lecturers, but would also include training for educational leaders and managers in order to enable ‘innovation, organizational ability and adaptivity’ (Colvin *et al.* 2015). A similar study in Europe found it will be necessary to identify the skills required to work in this field, and then to train and support educators to use analytics to support achievement (Ferguson *et al.* 2016a).

Learners will have less need than staff to know about the nuts and bolts of learning analytics. However, as their data are collected and analysed, they will need to be increasingly aware of their rights and responsibilities in this area. Having control over your data, or choosing to assign that control to others, is inextricably bound up with the need for knowledge about the value of that data and the purposes for which it could be used. Respondent 7137 considered that ‘It is essential that people are better equipped to understand their rights and how to control how it is used. Putting the owners of the data more central to the process makes it easier for people to accept its value’.

In the opinion of respondent 5140, ‘every single person must be enabled to decide who, when and how to proceed with the data’. In order for that to be possible, or even partly possible, learners and other stakeholders ‘need to be educated to deal properly with the choices concerned' (7936). This does not necessarily require technical training, but they do need to have the ability to ask the right questions. 'Although not all consumers of these services will have the skill necessary to understand the computer science and computation, it is necessary that they have the access to question the processes and assumptions under which the data is input, massaged, and output' (6616).

Society is increasingly reliant on data and algorithms (the sets of instructions that are used to process these data). This means that it is particularly important to ask 'Do staff and learners know how to use the analytics?' because this knowledge is relevant in many areas of life, not simply in an educational context. Algorithms are used to decide which online news and advertisements we see, which insurance package we are offered, whether our job applications can proceed to the next stage, and whether our applications for finance are successful. In order to understand the society in which we live, and in order to make an informed critique of many areas of life, we need a firm grounding in analytics and how they work.

Who is in control and how is this regulated?

The issue of understanding rights and responsibilities is associated with the important issues of data ownership and control. Large datasets are valuable and can be sold and traded. An individual or organization with control of educational data potentially also has the power to make a range of decisions about the learning and teaching process, and about how learners and teachers should act.

These issues are bound up with regulation of the field and how this regulation should be developed and enforced. Key areas for regulation identified by the VoF and LAEP studies were the protection, ownership and storage of data and the development of standards. Study participants also considered that policy would be needed in the areas of education, privacy, ethics and assessment.

Some VoF respondents saw control of personal data as crucial. They considered this control to be a fundamental human right that should not be dealt with piecemeal at local level, but should be a matter for the United Nations. 'It must be handled as a human right in the 21st century that every single person should have the power to decide, when + how + for what purpose + for which timeframe + ... his/her personal data can/cannot be used' (5140). This would imply a 'Legal framework governed by an international authority. Perhaps key concepts included in the fundamental human rights declaration' (0650).

In the absence of such far-reaching change, there is still a need for some degree of control of data. For example, student data could be sold to third parties, and the 'potential for misuse by e.g. insurance companies is very high' (1643). There is 'the threat of profit-motivated businesses trying to take control of this information, "de-commonising" it and selling it back to the individuals concerned' (7936)'. There is also the possibility that data could be used to monitor the process of learning and teaching in negative ways. 'If tracking and monitoring are used to foster and support education and learning, it might be desirable. If it is used to monitor and control and to enforce power it is not desirable’ (5297).

In practice, many stakeholders currently share control of data for many purposes. Educational data are already used at national and international levels, as in the case of the PISA studies that track pupils’ scholastic performance worldwide. Respondent 2692 noted that ‘It’s unlikely that governments or institutions will relinquish their control over learner data’. However, if governments controlled all data then educational institutions would lose the power to make informed choices. Nuanced contextual decisions based on local data would become impossible. ‘I think it is vital that educational establishments have control over the methods and tools that they use with their students’ (9792).

Schools and universities use data about students and teachers in order to exercise their own power – ‘there will be times when the institution needs to be able to decide where to share information about progress, attendance and exam results, for example, as part of a disciplinary process’ (7076).

External bodies, particularly commercial companies such as virtual learning environment (VLE) providers, are also likely to have access to analytic data. For example, Blackboard already offers an Analytics Suite that offers to ‘support tactical decisions with statistics’ and Desire2Learn offers Brightspace Insights to ‘turn raw data into knowledge’.

VoF respondents had concerns about commercial companies gaining access to student information, worrying that data could be handed over to companies without sufficient consideration of how those data might be used in an intrusive way to monitor behaviour and activities. Respondents were also worried that commercial power could be used to limit data access ‘Experience suggests that money talks and the large international companies that supply education succeed by keeping some of the analytics and data generated hidden behind intellectual property barriers’ (4820).

Moving from the corporate to the individual level, control of data could be placed in the hands of a variety of stakeholders. One choice would be the learner. ‘The key is to establish the notion that each of us own our own data: the companies do not. If this can be recognized, it moves the needle from our data being co-opted and sold back to us to a vision where the ultimate good can be achieved’ (6616). However, learners do not necessarily have the time and the inclination to make a string of decisions about how their data can and cannot be used in a variety of contexts, how it should be stored, who should have access, and how long it should be retained. Agreeing the terms of data use could become a tiresome process, completed without consideration, in the same way as users agree to terms of service without reading them and accept the use of cookies on their computers without investigating their purpose.

Another choice of data controller would be the teacher. ‘One of the purposes of LA is to empower the teachers to provide better learning for the individual learners. To know earlier what the learners problems are and to be able to address those problems' (5297). However, teachers have no more time than learners do to spend on considering data collection and storage. Realistically, there are potential problems with data management no matter who is in control, and whether or not the data are used for learning analytics:

> *I am not sure who *should* make use of such data: with care and education, it might be of direct value to learners. Teachers are likely better placed to make use of the data, but it is all too easy for it to be a tool for asserting power. It is even worse to put that control in the hands of system designers and programmers, thus embedding their assumptions and beliefs (or, just as likely, making use of whatever turns out to be easiest to program and capture).* (7473)

The possibility of embedding assumptions and beliefs, consciously or unconsciously, within analytics is bound up with the issue dealt with above of training staff and learners to use analytics, and encouraging them to discuss and reflect on this process. It is also bound up with issues of ethics, the 'systematizing, defending, and recommending concepts of right and wrong conduct' (Ferguson *et al.* 2016b).

There was widespread agreement amongst VoF respondents that there needs to be some form of regulation of ethical issues related to learning analytics, and that control of data has ethical implications. In parallel with the need for regulation in this area, there is also a need for awareness of how data are being used and how analytics function.

Many VoF respondents were vague about what the ethical concerns associated with learning analytics actually are, while stressing the need for an ethics policy, norms of good practice or ‘a robust ethical framework, supported by legislation’ (7076). Potential problems specifically mentioned include gaming the system, untrustworthy analytics, the creation of a two-tier educational system where only some have access to valid analytics, and the possibility that we could be ‘typecasting/stereotyping and even discriminating against certain individuals or groups on the basis of data’ (3462).

A body of literature in the field explores these issues in more depth. Ethical challenges include the location and interpretation of data; informed consent, privacy and the de-identification of data; and the classification and management of data (Slade and Prinsloo 2013). Slade and Prinsloo (Prinsloo and Slade 2013, Slade and Prinsloo 2014, Prinsloo and Slade 2015, Prinsloo and Slade 2016) have explored a range of these ethical issues, particularly those concerned with institutional surveillance, the right to opt out of the data-gathering process, and the responsibility of educational institutions to ensure appropriate support and guidance for students. Organisations are already beginning to address these issue by putting in place checklists and codes of practice (Sclater and Bailey 2015, Drachsler and Greller 2016, Rodríguez-Triana *et al.* 2016, Sclater 2016).

The use of ‘clear and understood ethical guidelines’ (4361) provides one way of dealing with these issues. An alternative approach would be for governments to specify that ‘institutional rules and regulations must exist and should meet certain criteria’ (5140).

This seems feasible, but 5140 also noted that if a government regulates the use of personal data ‘this would influence the independency of Universities in teaching and research’.

Whether the emphasis is on action at institutional or national level, work on ethics needs to be concerned not only with limitations on unacceptable conduct. If learning analytics can help institutions to provide the best possible support and guidance for their students, then institutions need to be willing to face the challenges in their students’ interests. At the same time, analytics will not work well unless they are based on accurate, complete and up-to-date information. Students therefore will have a responsibility to curate, correct and update their data – not just in their own interest, but also in the interest of other students in their cohort.

Learning can be a small-scale activity, involving an interaction between two individuals. Education is a larger enterprise, shaped by political and societal pressures, in which most individuals play only a small role. Learning analytics typically require large datasets, and so they also tend to function at this wider level. It is therefore important to ask ‘Who is in control and how is this regulated?’ in order to protect individual interests and to ensure that learning analytics are used to optimize, rather than to control, learning.

Future Directions

Learning analytics offer the potential for great changes to education. One of the eight LACE visions of the future provocations suggested that, in 2025,

> *Activity towards a learning goal is monitored, and analytics provide individuals with feedback on their learning process. This includes suggestions, including peer learners to contact, experts to approach, relevant content, and ways of developing and demonstrating new skills. Formative assessment is used to guide future progress, taking into account individuals' characteristics, experience and context, replacing exams that show only what students have achieved. Texts and other learning materials are adapted to suit the cultural characteristics of learners, revealed by analysis of their interactions. As a result, learners are personally engaged with their topics, and are motivated by their highly autonomous learning. The competences that they develop are valuable in a society in which collection and analysis of data are the norm.* (Griffiths *et al.* 2016a, p3)

Research and development work is currently underway in all these areas, and most of the experts who were invited to take part in the VoF study saw this as feasible future.

However, this is only one future amongst many. It will require engagement from a wide range of stakeholders to move education towards the desirable visions, and away from those in which use of data becomes obtrusive and unhelpful. The five-point checklist outlined in this chapter provides a straightforward starting point whether you are developing, deploying or just considering learning analytics. Addressing these five questions provides a firm basis for moving forward – what do we want to achieve, how will our analytics improve learning, where is the evidence, do staff and learners know how to use the analytics, who is in control and how is this regulated?

Acknowledgments

The Visions of the Future (VoF) study was funded by the European Commission Seventh Framework Programme as part of the LACE project: grant number 619424. The LAEP study was funded by the European Joint Research Centre in Seville.

References

Bakharia, A. and Dawson, S. (2011) 'SNAPP: A Bird's-Eye View of Temporal Participant Interaction', in *LAK11: 1st International Conference on Learning Analytics and Knowledge (27 February – 1 March)*, Banff, Canada.

Buckingham Shum, S. and Ferguson, R. (2012) 'Social learning analytics', *Educational Technology & Society*, 15(3), 3-26.

Colvin, C., Rogers, T., Wade, A., Dawson, S., Gasevic, D., Buckingham Shum, S., Nelson, K., Alexander, S., Lockyer, L., Kennedy, G., Corri, L. and Fisher, J. (2015) *Student Retention and Learning Analytics: A Snapshot of Australian Practices and a Framework for Advancement*, Sydney, Australia: Australian Government: Office for Learning and Teachinghe-analytics.com/wp-content/uploads/SP13-3249_-Master17Aug2015-web.pdf.

Dawson, S., Gašević, D., Siemens, G. and Joksimovic, S. (2014) 'Current state and future trends: a citation analysis of the learning analytics field', in *LAK 14*, Indianapolis, IN, ACM, 231-240.

Drachsler, H. and Greller, W. (2016) 'Privacy and analytics: it's a DELICATE issue a checklist for trusted learning analytics', in *Sixth International Conference on Learning Analytics & Knowledge*, Edinburgh, ACM.

Ferguson, R. (2012) *The State Of Learning Analytics in 2012: A Review and Future Challenges. Technical Report KMI-12-01*, Milton Keynes, UK: Knowledge Media Institute, The Open University http://kmi.open.ac.uk/publications/techreport/kmi-12-01.

Ferguson, R., Brasher, A., Clow, D., Cooper, A., Hillaire, G., Mittelmeier, J., Rienties, B., Ullmann, T. D. and Vuorikari, R. (2016a) *Research Evidence on the Use of Learning Analytics – Implications for Education Policy (EUR 28294)*, Seville, Spain: Joint Research Centre.

Ferguson, R., Brasher, A., Clow, D., Griffiths, D. and Drachsler, H. (2016b) 'Learning analytics: visions of the future, in *Sixth International Conference on Learning Analytics & Knowledge*, Edinburgh, ACM.

Ferguson, R., Hoel, T., Scheffel, M. and Drachsler, H. (2016b) 'Special section on ethics and privacy in learning analytics', *Journal of Learning Analytics*, 3(1).

Ferguson, R., Macfadyen, L. P., Clow, D., Tynan, B., Alexander, S. and Dawson, S. (2015) 'Setting learning analytics in context: overcoming the barriers to large-scale adoption', *Journal of Learning Analytics*, 1(3), 120-144.

Georgia State University (2015) 'Georgia State University – Dr. Tim Renick', [online], available: https://http://www.youtube.com/watch?v=9Z-hp5NrSBg.

Griffiths, D., Brasher, A., Clow, D., Ferguson, R. and Yuan, L. (2016a) *Visions of the Future of Learning Analytics: Horizon Report.* LACE Project.

Griffiths, D., Brasher, A., Clow, D., Ferguson, R. and Yuan, L. (2016b) *Visions of the Future: Horizon Report*, Bolton, UK: LACE projecthttp://www.laceproject.eu/d3-2-visions-of-the-future-2/.

Knight, S., Buckingham Shum, S. and Littleton, K. (2014) ‘Epistemology, assessment, pedagogy: where learning meets analytics in the middle space’. *Journal of Learning Analytics*, 1(2):23-47.

Kurzweil, R. (2005) *The Singularity Is Near*, London: Duckworth.

Macfadyen, L. P. and Dawson, S. (2012) 'Numbers are not enough. Why e-learning analytics failed to inform an institutional strategic plan', *Educational Technology & Society*, 15(3), 149-163.

McIntosh, N. E. (1979) 'Barriers to implementing research in Higher Education', *Studies in Higher Education*, 4(1), 77-86.

McNamara, D. S., Graesser, A. C., McCarthy, P. M. and Cai, Z. (2014) *Automated Evaluation of Text and Discourse with Coh-Metrix*, Cambridge: Cambridge University Press.

Pistilli, M. D., Arnold, K. E., Bethune, M. and Caasi, R. (2012) 'Using Academic Analytics to Promote Student Success', *EducauSE Review Online*, (July/Aug).

Prinsloo, P. and Slade, S. (2013) 'An evaluation of policy frameworks for addressing ethical considerations in learning analytics', in *Third International Learning Analytics & Knowledge Conference (LAK13)*, Leuven, Belgium, 8-12 April.

Prinsloo, P. and Slade, S. (2015) 'Student privacy self-management: implications for learning analytics', in Blikstein, P., Merceron, A. and Siemens, G., eds., *LAK '15*, Poughkeepsie, NY.

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

Rienties, B. and Toetenel, L. (2016) 'The impact of learning design on student behaviour, satisfaction and performance: a cross-institutional comparison across 151 modules', *Computers in Human Behavior*, 60, 333-341.

Rodríguez-Triana, M. J., Martínez-Monés, A. and Villagrá-Sobrino, S. (2016) 'Learning analytics in small-scale teacher-led innovations: ethical and data privacy issues', *Journal of Learning Analytics*, 3(1).

Sclater, N. (2016) 'Developing a Code of Practice for learning analytics', *Journal of Learning Analytics*, 3(1).

Sclater, N. and Bailey, P. (2015) *Code of Practice for Learning Analytics*Jisc http://www.jisc.ac.uk/guides/code-of-practice-for-learning-analytics.

Siemens, G., Gašević, D., Haythornthwaite, C., Dawson, S., Buckingham Shum, S., Ferguson, R., Duval, E., Verbert, K. and Baker, R. S. J. d. (2011) *Open Learning Analytics: An Integrated and Modularized Platform (Concept Paper)* SOLAR.

Slade, S. and Prinsloo, P. (2013) 'Learning analytics: ethical issues and dilemmas', *American Behavioral Scientist*.

Slade, S. and Prinsloo, P. (2014) 'Student perspectives on the use of their data: between intrusion, surveillance and care', in *European Distance and E-learning Network Research Workshop, 27-28 Oct*, Oxford, UK.

Turoff, M. (2002) 'The Policy Delphi' in Linstone, H. A. and Turoff, M., eds., *The Delphi Method: Techniques and Applications* 80-96.