Setting the scene – responding to a new set of choices

The Higher Education system in Australia is continually changing and evolving in response to the broader social and political landscape (Beer, Jones & Clark, 2012; Bennett & Hempsall, 2010). In recent years, the introduction, subsequent growth and broadening complexity of online learning - amongst other factors - has been the impetus for widespread exploration of the ways in which technology can be leveraged to improve higher education (ACODE, 2014; Wolff et al, 2013; Ferguson, 2012; Macfadyen & Dawson, 2010). Out of this exploration an important realisation has emerged that technological developments in the context of higher education are prone to generating more choices in terms of how things might be done (Gallagher, 2014; Chaloux & Miller, 2013).

Australia has a relatively well-resourced, sophisticated and mature higher education sector, with a strong commitment to scholarship of learning and teaching (Universities Australia, 2013). Despite this, an increasing range of choices around technology and data might be viewed as a challenge as much as an opportunity (Verbert et al, 2013; Hanna, 2000). At present, the sector is wrestling with how to balance attempts to take advantage of all that technology and data analysis have to offer with maintaining a realistic set of boundaries, which give clarity of purpose, promote productivity and reduce inertia on a day-to-day basis. It may seem overly simplistic, but every day learners, teachers and other stakeholders grapple with two practical questions that become more overwhelming as choice increases:

1. What should our time be spent on doing?
2. How should we allocate our resources?

Throughout the project the connected themes of choice and decision-making were a key point of focus. This is perhaps not surprising given that in many ways learning analytics can be thought of as the exploration, development and refinement of a new set of choices about how learning and teaching data is collected, integrated and used.

As the field of learning analytics matures, the focus of theory and practice is increasingly shifting from traditional post-hoc analysis to exploration of the possibilities that real-time data brings (Fiaidhi, 2014; Raca et al, 2014; Norris & Baer, 2013; Dawson, McWilliam & Tan, 2011; Baker & Yacef, 2009; Campbell, DeBlois & Oblinger 2007). Running alongside is an emerging focus on how computer-assisted personalisation, adaptivity and artificial intelligence might be developed and contextualised to meet higher education objectives (Baer et al, 2013; Chatti et al, 2012). Additionally, learning analytics presents new avenues for addressing ongoing themes such as the effectiveness of particular teaching styles (Baron & Harris, 2012) or approaches, like gamification (Tsui et al, 2014; Holman, Aguilar & Fishman, 2013; Camilleri et al, 2013) or whether the pedagogical intent of teachers is being realised through the learning process (Kennedy et al, 2014; Mirriahi & Dawson, 2013).

Even though the few examples above are just a fraction of where local and international research in the field is being focused, it is clear that there is both a richness and multiplicity to the field (van Harmelen & Workman, 2012) as well as a daunting variety (van Barneveld et al, 2012). Despite the flurry of activity, though, there remains a gap between the research that has taken place and the problems of most interest to institutions and academics (Siemens, 2012).

Overall, the current climate is one in which Australia's higher education institutions have a variety of promising and novel approaches to sift through when forming their strategic priorities. With so much data and so many options for handling and using it, learning analytics decision making is exceptionally complex - spanning pedagogy, data analysis, data infrastructure, project management and leadership expertise, amongst others (See Gasevic et al, 2014; Clow, 2013; Siemens, Dawson & Lynch, 2013; Norris & Baer, 2013; Ferguson, 2012).

Given that analytics more broadly, and learning analytics as a subfield, have such wide application it is important to set some boundaries around the focus of the project. As such, the project can be thought of as being primarily focused on:

1. the use of learning analytics for student retention purposes
2. seeking to understand those factors that impact on the implementation of learning analytics and how these vary across individual institutional contexts.

The next part of the report is a literature review which brings the focus of learning analytics to student retention. Chapters 2, 3 and 4 focus on describing the project's approach, method, outputs and findings in more detail. An exploratory project such as this often raises further questions, and the concluding stages of the paper articulate how this research can be built on over the coming months and years.

Learning analytics definitions and drivers

Learning analytics is most commonly defined as the "measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Long & Siemens, 2011). Ferguson (2012) notes that the definition above could be taken to cover the majority of educational research, and identifies two additional assumptions: that learning analytics make use of pre-existing, machine-readable data, and that its techniques can be used to handle 'big data', large sets of data that would not be practicable to deal with manually.

In addition to the rise of online learning and political concerns (e.g. performance management, metrics and quantification), which are well-known drivers across most facets of Higher Education, 'big data' is an important driver (Clow, 2013; Ferguson, 2012), that is perhaps less well-understood. Gartner Inc. (2015) define big data as "high-volume, high-velocity and high-variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making". Growth in big data is driving many of the emerging tools and methods of learning analytics.

Berman (2013) writes of ten ways in which big data might be distinguished from small data. It is important to be aware they are not exhaustive or definitive, but the value of these lies in supporting people to quickly conceptualise how big data is changing what is possible and what the potential of learning analytics might be.

Table 1: Differences between big and small data (Adapted from Berman, 2013)

	Big Data	Small Data
Goals	Usually designed with a goal in mind, but the goal is flexible and the questions posed are protean. There really is no way to completely specify what the Big Data resource will contain and how the various types of data held in the resource will be organized, connected to other data resources, or usefully analysed. Nobody can specify, with any degree of confidence, the ultimate destiny of any Big Data project; it usually comes as a surprise.	Usually designed to answer a specific question or serve a particular goal
Location	Typically spread throughout electronic space, typically parcelled onto multiple Internet servers, located anywhere on earth.	Typically, small data is contained within one institution, often on one computer, sometimes in one file.
Structure	Must be capable of absorbing unstructured data (e.g., such as free-text documents, images, motion pictures, sound recordings, physical objects). The subject matter of the resource may cross multiple disciplines, and the individual data objects in the resource may link to data contained in other, seemingly unrelated, Big Data resources.	Ordinarily contains highly structured data. The data domain is restricted to a single discipline or sub-discipline. The data often comes in the form of uniform records in an ordered spreadsheet.
Preparation	The data comes from many diverse sources, and it is prepared by many people. People who use the data are seldom the people who have prepared the data.	In many cases, the data user prepares their own data, for their own purposes.
Longevity	Big Data projects typically contain data that must be stored in perpetuity. Ideally, data stored in a Big Data resource will be absorbed into another resource when the original resource terminates. Many Big Data projects extend into the future and the past (e.g., legacy data), accruing data prospectively and retrospectively.	When the data project ends, the data is kept for a limited time (seldom longer than 7 years, the traditional academic life span for research data) and then discarded.
Measurement	Many different types of data are delivered in many different electronic formats. Measurements, when present, may be obtained by many different protocols. Verifying the quality of Big Data is one of the most difficult tasks for data managers.	Typically, the data is measured using one experimental protocol, and the data can be represented using one set of standard unit
Reproducability	Replication of a Big Data project is seldom feasible. In most instances, all that anyone can hope for is that bad data in a Big Data resource will be found and flagged as such.	Projects are typically repeatable. If there is some question about the quality of the data, reproducibility of the data, or validity of the conclusions drawn from the data, the entire project can be repeated, yielding a new data set.
Stakes	Big Data projects can be obscenely expensive. A failed Big Data effort can lead to bankruptcy, institutional collapse, mass firings, and the sudden disintegration of all the data held in the resource.	Project costs are limited. Laboratories and institutions can usually recover from the occasional small data failure.

	Though the costs of failure can be high in terms of money, time, and labour, Big Data failures may have some redeeming value. Each failed effort lives on as intellectual remnants consumed by the next Big Data effort.	
Introspection	Unless the Big Data resource is exceptionally well designed, the contents and organization of the resource can be inscrutable, even to the data managers. Complete access to data, information about the data values, and information about the organization of the data is achieved through a technique herein referred to as introspection.	Individual data points are identified by their row and column location within a spreadsheet or database table (see Glossary item, Data point). If you know the row and column headers, you can find and specify all of the data points contained within.
Analysis	With few exceptions, such as those conducted on supercomputers or in parallel on multiple computers, Big Data is ordinarily analyzed in incremental steps. The data are extracted, reviewed, reduced, normalized, transformed, visualized, interpreted, and re-analysed with different methods.	In most instances, all of the data contained in the data project can be analyzed together, and all at once.

Distinctive features of learning analytics

There have notable attempts to disambiguate learning analytics from other forms of analytics, such as by Clow (2013), who pragmatically pointed out the focus on 'learning' is a defining characteristic. Long and Siemens (2011) suggested that learners and faculty were the primary beneficiaries of learning analytics, whereas, academic analytics was more concerned with managerial and institutional concerns.

Ochoa and colleagues (2014:5) allude to the presence of grey areas by observing "learning analytics is a new, expanding field that grows at the confluence of learning technologies, educational research, and data science". Helpfully, they continue on to state that: "Over time researchers and practitioners with different backgrounds and methodologies have tried to solve two simple but challenging questions:

1. How do we measure the important characteristics of the learning process?
2. And how do we use those measurements to improve it?

Despite efforts to articulate a distinctiveness for learning analytics, in reality the field is still new enough that in this project's experience such distinctions are not well-understood across the sector. As such, this project was mostly interested in analytics that could be applied to the issue of student retention.

Learning analytics objectives

It is well understood that learning and the environments in which it takes place are exceptionally broad in nature. This means that the objectives or applications of learning analytics are open to ongoing interpretation. One practical summary of learning objectives is offered on the Edutech Wiki (2013):

1. For individual learners to reflect on their achievements and patterns of behaviour in relation to others;
2. As predictors of students requiring extra support and attention;
3. To help teachers and support staff plan supporting interventions with individuals and groups;
4. For functional groups such as course teams seeking to improve current courses or develop new curriculum offerings;
5. For institutional administrators taking decisions on matters such as marketing and recruitment or efficiency and effectiveness measures; and
6. For comparisons between systems (state, regional, national and international)

An interesting way of exploring the impact that learning analytics might have is reported on by Draschler, Stoyanov & Specht (2014). They conducted a group concept mapping exercise (n = 31, plus an additional pool for sorting) that explored what participants in their study felt would be the impact of learning analytics on the Dutch higher education system. They statements gathered were sorted into seven clusters: 1. Student Empowerment, 2. Personalization, 3. Research & Learning Design, 4. Teacher Empowerment, 5. Feedback & Performance, 6. Risks, and 7. Management & Economics. Further descriptions and example statements can be found in their paper.

Learning analytics processes and methods

It has been noted by van Harmelen and Workman (2012) learning analytics sits at the intersection of several different fields and is characterised by a rich multiplicity of methods and approaches. Although there is a wide degree of variation in the way that analytics might be conducted around learning, as Bichsel (2012) observes, analytics can be conceptualised as having a common process. On behalf of Educause she articulates this process as a cycle with five stages that keep looping as refinement takes place:

1. Identify a strategic question
2. Find or collect relevant data to the question
3. Analyse the data with a view to prediction and insight
4. Form and present the data in understandable and actionable ways
5. Feedback into the process of addressing the strategic question and identifying new ones

Another process is set out by Based on a learning analytics process Campbell and Oblinger (2007), who propose five steps: capture, report, predict, act and refine.

Although these processes make good sense looking at them in isolation could reinforce confusion in the sector about how learning analytics differs from current approaches to optimising learning and the environments in which it occurs. This is what makes the idea of ‘big data’ so pivotal.

Reference models

A couple of different authors have developed reference models that help people understanding the various dimensions of learning analytics and the different categories of 'things' that sit in those dimensions. The first by Chatti et al (2012) utilises the simple what, why, who and how prompts to organise the different dimensions. The paper describing this model is accompanied by a companion piece by Ferguson (2012), which provides an overview of the context and drivers for learning analytics. In association, both form an excellent general introduction to the promises and challenges of learning analytics.

A second model presented by Fiaidhi (2014) presents what the author refers to as a comprehensive learning analytics architecture. One of the major strengths of this model of this model and the accompanying paper is the important distinction between structured and unstructured data and how each might be handled and used in the context of learning analytics.

The two models described above have much to offer in facilitating the development of common understandings about what learning analytics is and what makes it distinct.

Examples

It can be difficult for people new to learning analytics (and especially the 'big data' side of it) to immediately grasp what learning analytics look like or how they work given the complexity of the two models described above. Papers like Verbert et al's (2013), summary of research into dashboards are a crucial addition to the field because they both articulate and situate concrete, accessible examples of the type of methods and approaches being explored across the spectrum of learning analytics (Other examples include Clow, 2013 and Norris & Baer, 2012). Verbert and colleagues organise their examples around the following:

Relevant user actions

- **Artefacts** (e.g. blog post, tweets etc.)
- **Social interaction** (e.g. speech, ratings of tweets)
- **Resource use**
- **Time spent doing something**
- **Test and self-assessment results**

Capture of data

- **Physical sensors** (e.g. cameras, microphones)
- **Virtual sensors** (e.g. application and event logs)
- **Manual reporting** (e.g. observations by teachers)

Sense-making

- **Desktops and laptops**
- **Tablets**
- **Mobile devices**
- **Tabletops**

Evaluation of dashboard apps

- **Effectiveness**
- **Efficiency**
- **Usefulness and/or useability**

Building knowledge and capacity

One of the more positive aspects of learning analytics as an emerging field is that there has been strong dedication to organising knowledge in a practical and helpful way. This operates on a number of levels.

- Dedicated journals (e.g. Journal of Learning Analytics).
- Proceedings from conferences like the annual Learning Analytics and Knowledge events. See http://dl.acm.org/citation.cfm?id=2723576 for the recently released 2015 proceedings, which are organised into session topics. The Table of Contents also links to previous proceedings.
- Scientometric papers (e.g. Ochoa et al, 2014; Dawson et al, 2014), mapping the development of literature in the field.

These three avenues alone offer much to individuals, groups and institutions across the sector in terms of mapping out the potential uses of learning analytics across contexts. One of the biggest challenges at present is that many of these papers operate under the assumptions and constraints of their respective research contexts and how the cost, benefit, scalability and generalisability of particular approaches and methods translates to new contexts and constraints can be unclear (Buerck & Mudigonda, 2014; Beer, Jones & Clark, 2012) or not yet explored. It is notable that more papers are emerging that are focused on synthesising different research and knowledge domains (LAK, 2015) within learning analytics and the hope is that this will continue the process of developing the accessibility and usefulness of learning analytics.

Latest developments

This section to be included is a summary of the latest research and from the recent LAK 2015 conference. Given the very recent release of these materials this will need to be an addition over the next few weeks.

The Australian context and key focus areas

Clearly, there is much happening internationally in the learning analytics space. Readers might recall that the learning analytics process articulated by Norris & Baer (2013) starts with the identification of strategic questions so one of the pivotal responsibilities of the project was to look at the Australian context and identify key issues, especially in views of the fact that political concerns are recognised as one of the key drivers for learning analytics (Clow, 2013; Ferguson, 2012). This section will commence with a brief overview of the Australian system, a look at key some target groups for participation and retention and then will explore more closely how the issue of student retention intersects with learning analytics.

Universities Australia (2013) identify four trends that are driving change in the Australian higher education system (and have clear connections with learning analytics). These are:

1. The emergence of the digital economy and new technology;

2. Increasing globalisation and the possibilities of the Asian century;
3. Economic and industrial restructuring as the nation responds to the resources boom; and,
4. The need to improve productivity with universities central to the national innovation effort.

Student retention has become a major focus in the higher education sector over the last 10 years, and in particular in response to the Review of Australian Higher Education, better known as the 'Bradley Review' (Bradley et al., 2008). The Bradley Review includes high targets: "the target proposed for higher education is that 40 per cent of 25- to 34-year-olds will have attained at least a bachelor-level qualification by 2020. This will be quite testing for Australia as current attainment is 29 per cent." Achieving these targets will require not only increasing the rate of enrolment but also, critically, improving student retention. Student retention, either within a unit or a course, can vary significantly across institutions and jurisdictions in Australia. In 2010 student retention averaged 86.6 per cent nationally, with the lowest rate being 71.0 per cent in the Northern Territory (NT) and the highest being 88.8 per cent in New South Wales (NSW) (DIISCCRTE, 2012).

The Bradley Review also set the target that: "by 2020, 20 per cent of undergraduate enrolments in higher education should be students from low socio-economic backgrounds". Student from low socio-economic backgrounds are one of a number of official equity groups. Currently, these are: students from non-English speaking background, students with a disability, women in non-traditional areas, low SES students, regional and remote students, and Indigenous students (Koshy, 2014; DIICCSRTE, 2012).

Equity groups have traditionally participated in higher education at a proportionally lower rate than their presence in the broader population. Table x is adapted from a recent report by Koshy (2014), which draws on longitudinal data from DIISCCRTE (2012). It illustrates that on top of a 20% increase in overall student enrolments in the five years from 2007 to 2012 there have been specific improvements in the proportional representation of most equity groups, with remote students being the major exception, having only reported about 7% growth in the five year period.

Table 2: Enrolment numbers and overall share of equity groups in Australian higher education (Adapted from Koshy, 2014)

Group	Enrolment numbers 2012	Enrolment growth from 2007-2012	Overall share of enrolments 2012	Growth in share 2007-2012
National*	**634,434**	**20.0%**	**n/a**	**n/a**
Non-English Speaking Background	21,289	27.5%	3.4%	6.3%
Disability	33,220	43.5%	5.2%	13.6%
Indigenous	9,005	31.9%	1.4%	7.7%
Low SES	109,784	27.8%	17.3%	6.8%
Regional	121,476	20.5%	19.1%	0.0%
Remote	5,804	6.9%	0.9%	-10.0%

*** 38 Universities representing 93.4% of Australia's higher education enrolments**

In addition to lower participation equity groups generally have lower rates of retention, with a 76.7 per cent rate of retention nationally in 2010, with the NT again having the lowest rate at 59.9 per cent and the Australian Capital Territory the highest at 80.9 per cent (DIICCSRTE, 2012).

Whilst mostly modest gains have generally been made to the proportional participation of equity students in higher education it is acknowledged that there is much work to be done. In a recent review, Behrendt and colleagues (2012), point out Aboriginal and Torres Strait Islander people comprised 2.2 per cent of the overall population, yet made up only 1.4 per cent of student enrolments in 2010, including only 1.1 per cent of higher degree by research enrolments. Disparity carries over to staffing, with Aboriginal and Torres Strait Islander people representing 0.8 per cent of all full-time equivalent academic staff and 1.2 per cent of general university staff in 2010 (Behrendt et al, 2012)

Similar to the Bradley review, Behrendt and her colleagues recommended ambitious, but important, targets: “For retention and completion rates of students, the panel has recommended that the parity target be set to match retention and completion rates of non-Indigenous students”. A background paper for the review, drawing heaving on previous work by the Indigenous Higher Education Advisory Committee (2006), identifies a variety of challenges that need to be met in order to improve Indigenous participation and success in higher education. Important factors identified as contributing to Aboriginal and Torres Strait Islander students’ premature withdrawal from studies included financial pressures, social or cultural alienation caused by the academic demands of study, and insufficient academic support (Pechenkina & Anderson, 2011).

In addition to recent reviews, patterns of investment and notable strategic initiatives in higher education emphasise the importance of student retention. As described by Universities Australia (2013: 16):

> “The Australian Government currently supports the participation of under-represented groups in higher education by funding enabling and foundation programs. These initiatives help prepare students for higher education study and, through the Higher Education Participation and Partnerships Program, assist universities to support students from low SES backgrounds, often in partnership with schools, vocational education providers, other universities, government, and community groups. In addition, each university has a range of programs to encourage people from under-represented groups to enrol in higher education, alternative entry programs, transition programs and study support programs.”

One of the great hopes for learning analytics is that it can impact on multiple levels across the sector. This overview of the policy context illustrates that keeping track of progress requires access to a variety of data, whose reporting often lags significantly behind real time. Even before the commencement of discussion of the application of learning analytics to retention in the context of individual institutions, it is apparent that some of the methods of learning analytics are of prospective benefit to policymakers as well.

Bringing the learning analytics focus to student retention in the context of success and engagement

A defining characteristic of this project is that it is a strategic commissioned project which reflects the Australian Government’s interest in the application of learning analytics for student retention. Throughout the project, and in the literature (Clarke, Nelson & Stoodley, 2013; Willcoxson et al, 2011), it has become apparent that student retention is increasingly being subsumed into broader activities and thinking around student success and student engagement. Thus, there was an inherent tension for the project in acknowledging the conceptualisation of student retention in the context of success and engagement and staying focused specifically on the issue of retention.

A key theme is how analytics can *specifically* facilitate retention, progression and completion across the life-cycle, and this relates firstly to the First Year Experience (FYE)

(James et al., 2010) and secondly to the ways in which analytics can be applied to what Kift et al. (2010) call ‘transition pedagogy’ (see Nelson et al., 2012; Kift, 2009). This has been a particularly important issue in response to the Bradley Review (Bradley et al., 2008), which in turn is part of a broader agenda that in other national contexts is sometimes called ‘widening participation’ (Chowdry et al., 2012; Thomas, 2001). Although there has been a strong focus on supporting students through their early interactions with higher education, Willcoxson et al’s (2011) study concluded that the issue of retention and attrition in later years needs additional attention. One of the key challenges for learning analytics is to create scalable opportunities for expanding the focus from first year to all years, preferably without a concomitant increase in cost.

The academic and non-academic factors that can influence retention are complex and varied (Clarke, Nelson & Stoodley, 2013); an assertion supported by a study (n = 7486) of business students across six Australian universities, in which Willcoxson and colleagues (2011:1) reported the following:

> “data strongly indicates that factors related to attrition are generally university-specific and reflect both student characteristics and their responses to the specific institutional culture and environment. The only attrition triggers which span most universities and most years of study are ‘lack of a clear reason for being at university’ and ‘the feeling of having insufficient ability to succeed at university’.”

Studies have also shown that online courses have higher attrition rates than traditional face to face classrooms (Diaz, 2000). Investigations into the differences between ‘click’ and ‘brick’ establishments suggest several causal factors, however, there are conflicting results among studies as to which factor has the biggest impact on student dropout rates (Dekker, Pechenizkiy & Vleeshouwers, 2009; Rivera & Rice, 2002; Diaz, 2000). Possible factors include differences in the student demographic as there tends to be more students from lower socio-economic backgrounds with less formal educational qualifications enrolled in online courses. There can also be difficulties with effectively using the technologies needed for online study, increased time constraints and less academic ‘preparedness’ for study. Due to lack of face-to-face contact, students can also feel isolated and unsupported by their tutors or online peers (Frankola, 2002).

For reasons of space, this a just a brief overview of some studies that illustrate themes of focus where student retention is concerned. There are numerous other studies in the literature that are highlighted by recent OLT and ALTC projects on student retention (see Clarke, Nelson & Stoodley, 2013; Willcoxson et al, 2011). Similarly, there are a wide variety of studies in the learning analytics literature that could be seen to have at least some connection to student retention, with Signals at Purdue University (Arnold & Pistilli, 2012; Campbell, 2007) a noted example, though many more are emerging (see LAK2015 proceedings for a selection as well as Norris & Baer, 2012).

Thinking more holistically, Tinto (2009) suggests that to be serious about student retention, universities need to recognise that the roots of student attrition lie not only in their students and the situation they face, but also in the very character of the educational settings in which they ask students to learn. If one goes back to the learning analytics definitions of "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 & Long, 2011), it becomes clear that student retention (and success and engagement) have a natural affinity with learning analytics.

Tinto (2009: 3) identifies four conditions of student success:

1. Expectations – students are more likely to persist and graduate in settings that hold high and clear expectations for student achievement;
2. Support – support (including academic and social) is a condition that promotes retention;
3. Feedback – students are more likely to succeed in settings in which information about student progress is not only collected by fed back in a timely manner to teachers, staff and students, in forms that enable them to use that information to promote student success; and
4. Involvement – the more students are academically and socially involved (or engaged), the more likely they are to persist and graduate.

Clarke, Nelson, and Stoodley (2013: 96) take this idea further and add more detail in their Student Engagement Success and Retention Model (SESR-MM), by including the following categories:

- Learning – assessment, curricula, teaching practices, pedagogical styles
- Supporting - information, services, resources, 'people rich' advice, advocacy and peer support
- Belonging – interaction, inclusive activities, identity development/formation opportunities
- Integrating – academic literacies, personal literacies
- Resourcing – staff development, evidence base, communication, learning environments

Both Tinto's four conditions, and especially Clarke and colleagues categories are potentially measurable, and this is of course where learning analytics comes in and what was of key interest of this project.

References

ACODE (2014). *Benchmarks for Technology Enhanced Learning*. Retrieved 12 May, 2015 from http://www.acode.edu.au/pluginfile.php/579/mod_resource/content/3/TEL_Benchmarks.pdf

Arnold, K. (2010). Signals: Applying academic analytics. *Educause Review Online*. Retrieved March 12, 2015 from http://www.educause.edu/ero/article/signals-applying-academic-analytics

Arnold, K., Lonn, S., & Pistilli, M. (2014). An exercise in institutional reflection: The Learning Analytics Readiness Instrument (LARI). *Proceedings of the 4th International Conference on Learning Analytics and Knowledge (LAK '14)*, Indianapolis, IN, USA. doi:10.1145/2567574.2567621

Arnold, K. & Pistilli, M. (2012). Course signals at Purdue: Using learning analytics to increase student success, *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge (LAK '12)*, Vancouver, British Columbia, Canada. doi:10.1145/2330601.2330666

Baer, L., Norris, D., Duin, A., & Brodnick, R. (2013). Crafting transformative strategies for personalized learning/analytics. *Proceedings of the 3rd International Conference on Learning Analytics and Knowledge (LAK '13),* Leuven, Belgium. doi:10.1145/2460296.2460354

Baker, R., & Yacef, K. (2009). The state of educational data mining in 2009: A review and future visions. *Journal of Educational Data Mining*, 1 (1), 3-17. Retrieved April 12, 2015 from \
http://www.educationaldatamining.org/JEDM/index.php/JEDM/article/download/8/2

Balacheff, N., & Lund, K. (2013). Multidisciplinarity vs. multivocality: The case of "Learning Analytics". *Proceedings of the 3rd International Conference on Learning Analytics and Knowledge (LAK '13),* Leuven, Belgium. doi:10.1145/2460296.2460299

Baron, J., & Harris, R. (2012). Open academic analytics initiative: Leveraging openness to improve learner success. *EDUCAUSE Learning Initiative 2012 Annual Meeting.* Retrieved May 12, 2015 from http://www.educause.edu/events/educause-learning-initiative-2012-annual-meeting/2012/open-academic-analytics-initiative-leveraging-openness-improve-l

Beer, C., Jones, D. & Clark, D. (2012). Analytics and complexity: Learning and leading for the future. *Proceedings Future Challenges: Sustainable Futures, ascilite, Wellington, NZ.* Retrieved April 13, 2015 from http://eprints.usq.edu.au/23092/2/Beer_Jones_Clark_ascilite_2012_PV.pdf

Behrendt, L., Larkin, S., Griew, R., & Kelly, P. (2012). Review of Higher Education Access and Outcomes for Aboriginal and Torres Strait Islander People: Final Report. Canberra: Australian Government. Retrieved May, 12, 2012 from http://docs.education.gov.au/documents/review-higher-education-access-and-outcomes-aboriginal-and-torres-strait-islander-people-0

Berman, J. (2013) *Principles of big data: Preparing, sharing, and analyzing complex information*. Burlington, MA: Morgan Kaufmann/Elsevier.

Bichsel, J. (2012). *Analytics in higher education; Barriers, progress, and recommendations*. Louisville, CO: EDUCAUSE Center for Applied Research. Retrieved April 14, 2015 from http://net.educause.edu/ir/library/pdf/ERS1207/ers1207.pdf

Bradley, D., Noonan, P., Nugent, H., & Scales, B. (2008). Review of Australian Higher Education: Final Report. Canberra: Department of Education, Employment and Workplace Relations. Retrieved May, 12, 2015 from www.mq.edu.au/pubstatic/public/download.jsp?id=111997

Buckingham Shum, S., & Deakin Crick, R. (2012). Learning dispositions and transferable competencies: Pedagogy, modelling and learning analytics. *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge (LAK '12)*, Vancouver, British Columbia, Canada. doi:10.1145/2330601.2330629

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

Buerck, J., & Mudigonda, S. (2014). A resource-constrained approach to implementing analytics in an institution of higher education: An experience report. *Journal of Learning Analytics*, 1(1), 129–139.

Camilleri, V., de Freitas, S., Montebello, M., & McDonagh-Smith, P. (2013). A case study inside virtual worlds: Use of analytics for immersive spaces. *Proceedings of the 3rd International Conference on Learning Analytics and Knowledge (LAK '13),* Leuven, Belgium. doi:10.1145/2460296.2460341

Campbell, J. (2007). Utilizing student data within the course management system to determine undergraduate student academic success: An exploratory study. Purdue University. Retrieved 12 May, 2015 from http://docs.lib.purdue.edu/dissertations/AAI3287222/

Campbell, J., DeBlois, P., & Oblinger, D. (2007). Academic analytics: A new tool for a new era, *Educause Review*, July/August 2007. Retrieved May 12, 2015 from https://net.educause.edu/ir/library/pdf/ELIWEB0710.pdf

Campbell, J., and Oblinger, D. (2007) Academic analytics: White paper. Educause. Retrieved 12 May, 2015 from http://net.educause.edu/ir/library/pdf/pub6101.pdf

Chaloux, B., & Miller, G. (2013). E-learning and the transformation of higher education. Chapter 1 (pp. 3-23) in G. Miller, M. Benke, B. Chaloux, L. Ragan, R. Schroeder, W. Smutz, Wayne, K. Swan, (Eds.) *Leading the e-Learning transformation in higher education: meeting the challenges of technology and distance education*. Stirling, VA: Stylus Publishing.

Chatti, M., Dyckhoff, A., Schroeder, U., & Thüs, H. (2012). A reference model for learning analytics. *International Journal of Technology Enhanced Learning*, 4(5/6), 318–331.

Chowdry, H., Crawford, C., Dearden, L., Goodman, A., & Vignoles, A. (2013), Widening participation in higher education: analysis using linked administrative data. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 176: 431–457. doi: 10.1111/j.1467-985X.2012.01043.x

Clarke, J., Nelson, K., & Stoodley, I. (2013). The place of higher education institutions in assessing student engagement, success and retention*: Proceedings Higher Education Research and Development Society of Australasia*, Auckland, New Zealand. Retrieved May 12, 2015 from http://eprints.qut.edu.au/60024/2/60024.pdf

Clow, D. (2012). The learning analytics cycle: Closing the loop effectively. *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge (LAK '12), Vancouver, British Columbia, Canada.* doi:10.1145/2330601.2330636

Clow, D. (2013). MOOCs and the funnel of participation. *Proceedings of the 3rd International Conference on Learning Analytics and Knowledge (LAK '13),* Leuven, Belgium. doi:10.1145/2460296.2460332

Corrin, L., Kennedy, G., & Mulder, R. (2013). Enhancing learning analytics through understanding the needs of teachers. *Proceedings 'Electric Dreams', 30th ascilite Conference,* Sydney, Australia. Retrieved May 12, 2015 from http://www.ascilite.org/conferences/sydney13/program/papers/Corrin.pdf

Heathcote, E., & Dawson, S. (2005) Data mining for evaluation, benchmarking and reflective practice in a LMS. *Proceedings e-Learn 2005: World conference on e-Learning in corporate, government, healthcare & higher education*, Vancouver, Canada. Retrieved April 13, 2015 from http://eprints.qut.edu.au/2368/1/2368.pdf

Dawson, S. (2010). "Seeing" the learning community: An exploration of the development of a resource for monitoring online student networking. *British Journal of Educational Technology*, 41, 736-752.

Dawson, S., Bakharia, A., Lockyer, L., & Heathcote, E. (2011). Seeing networks; visualising and evaluating student learning networks. Final Report 2011. Surrey Hills, NSW: Australian Learning and Teaching Council. Retrieved 10 May, 2015 from http://research.uow.edu.au/content/groups/public/@web/@learnnet/documents/doc/uow115678.pdf

Dawson, S., Gašević, D., Siemens, G., & Joksimovic, S. (2014). Current state and future trends: A citation network analysis of the learning analytics field. *Proceedings of the 4th International Conference on Learning Analytics and Knowledge (LAK '14)*, Indianapolis, IN, USA. doi:10.1145/2567574.2567585

Dawson, S., Tan, J., & McWilliam, E. (2011). Measuring creative potential: Using social network analysis to monitor a learners' creative capacity. *Australian Journal of Educational Technology*, 27(6), 924-942.

Dekker, G., Pechenizkiy, M. and Vleeshouwers, J. (2009) Predicting students' drop out: a case study. *Proceedings of the 2nd International Conference on Educational Data Mining (EDM '09),* Cordoba, Spain. *http://www.educationaldatamining.org/EDM2009/uploads/proceedings/dekker.pdf*

Diaz, D. (2000). *Comparison of student characteristics, and evaluation of student success, in an online health education course*. Unpublished doctoral dissertation, Nova Southeastern University. Retrieved 12 May 2015 from http://home.earthlink.net/~davidpdiaz/LTS/pdf_docs/dissertn.pdf

Department of Industry, Innovation, Climate Change, Science, Research and Tertiary Education (DIICCSRTE) (2012). *2011 full year higher education student statistics Appendix 2 – Equity Groups.* Canberra: Australian Government. Retrieved 18 June, 2013 from http://www.innovation.gov.au/HigherEducation/HigherEducationStatistics/StatisticsPublications/Pages/2011StudentFullYear.aspx

Department of Industry, Innovation, Climate Change, Science, Research and Tertiary Education (DIICCSRTE) (2012). *2011 full year higher education student statistics Appendix 4 - attrition, progress and retention.* Canberra: Australian Government. Retrieved 14 June 2013 from http://www.innovation.gov.au/HigherEducation/HigherEducationStatistics/StatisticsPublications/Pages/2011StudentFullYear.aspx

Department of Industry, Innovation, Climate Change, Science, Research and Tertiary Education (DIICCSRTE). (2013a). *Students: selected higher education statistics 2012 (Appendix 2: equity data).* Canberra: DIICCSRTE.

Department of Industry, Innovation, Climate Change, Science, Research and Tertiary Education (DIICCSRTE). (2013b). *Moving to an enhanced indicator of higher education students' socio-economic status*. Canberra: DIICCSRTE.

Drachsler, H., Stoyanov, S., & Specht, M. (2014). The impact of learning analytics on the Dutch education system. *Proceedings of the 4th International Conference on Learning Analytics and Knowledge (LAK '14)*, Indianapolis, IN, USA. doi:10.1145/2567574.2567617

EDUCAUSE (2010). *7 Things you should know about analytics.* Retrieved May 12, 2015 from http://www.educause.edu/ir/library/pdf/ELI7059.pdf

EDUCAUSE Center for Applied Research (ECAR) (2012). *Analytics Maturity Index for Higher Education*. Retrieved May 12, 2015 from http://www.educause.edu/ecar/research-publications/ecar-analytics-maturity-index-higher-education

EduTech Wiki (2013). *Learning analytics*. Retrieved 14 June, 2013 from http://edutechwiki.unige.ch/en/Learning_analytics#Introduction

Ferguson, R., (2012). Learning analytics: drivers, developments and challenges. *International Journal of Technology Enhanced Learning,* 4(5/6), 304–317.

Ferguson, R. & Buckingham Shum, S. (2011). Learning analytics to identify exploratory dialogue within synchronous text chat. *Proceedings of the 1st International Conference on Learning Analytics and Knowledge (LAK'11)*, Banff, Canada. doi:10.1145/2090116.2090130

Ferris, J. (2008). *How to compete on analytics: The analytical centre of excellence*. SAS White Paper. Retrieved May 12, 2015 from http://www.sas.com/resources/whitepaper/wp_6426.pdf

Fiaidhi, J. (2014). The next step for learning analytics. *IT PRO/Institute of Electrical and Electronics Engineers*, September/October 2014. Retrieved May 12, 2015 from https://www.computer.org/csdl/mags/it/2014/05/mit2014050004.pdf

Frankola, K. (2001). *Why online learners drop out*. Retrieved May 12, 2015 from http://www.workforce.com/articles/why-online-learners-drop-out

Gartner Inc. (2015) *IT glossary: Big data*. Retrieved April 15, 2015 from http://www.gartner.com/it-glossary/big-data

Gallagher, M. (2014). Micro-economic reform of the Australian higher education industry: Implications of the Abbott Government's Budget of 13 May 2014. *Address to the EduTECH Higher Education Leaders Congress,* Brisbane, Australia. Retrieved May 10, 2015 from https://go8.edu.au/sites/default/files/docs/article/edutech_presentation_-_4_june_2014-pdf_version.pdf

Gašević, D., Mirriahi, N., Long, P., & Dawson, S. (2014). Editorial – inaugural issue of the Journal of Learning Analytics. *Journal of Learning Analytics*, 1(1), 1–2.

Goldstein, P., & Katz, R. (2005). Academic analytics: The uses of management information and technology in higher education. *ECAR Research Study, Vol. 8*. Retrieved May 10, 2015 from http://www.educause.edu/library/resources/academic-analytics-uses-management-information-and-technology-higher-education

Greller, W., & Drachsler, H. (2012). Translating learning into numbers: A generic framework for learning analytics. Educational Technology & Society, 15(3), 42–57.

Hanna, D. (2000). Higher education in an era of digital competition: choices and challenges. Madison, WI: Atwood Publishing.

Holman, C., Aguilar, S., & Fishman, B. (2013). GradeCraft: what can we learn from a game-inspired learning management system. *Proceedings of the 3rd International Conference on Learning Analytics and Knowledge (LAK '13),* Leuven, Belgium. doi:10.1145/2460296.2460350

Indigenous Higher Education Advisory Council (IHEAC) (2006*). Improving Indigenous outcomes and enhancing Indigenous culture and knowledge in Australian higher education*. Retrieved April 12, 2015 from http://www.voced.edu.au/content/ngv30547

James, R., Krause, K-L., & Jennings, C. (2010). *The first year experience in Australian universities: Findings from 1994 to 2009*. Centre for the Study of Higher Education, Melbourne: University of Melbourne. Retrieved May 10, 2015 from http://www.cshe.unimelb.edu.au/research/experience/docs/FYE_Report_1994_to_2009.pdf

Kennedy, G., Corrin, L., Lockyer, L., Dawson, S., Williams, D., Mulder, R., Khamis, S. & Copeland, S. (2014). Completing the loop: returning learning analytics to teachers. *Proceedings Rhetoric and Reality: Critical perspectives on educational technology, 31st ascilite Conference*, Dunedin, New Zealand. Retrieved May 12, 2015 from http://www.academia.edu/12074024/Completing_the_loop_returning_learning_analytics_to_teachers

Kift, S. (2009). *Articulating a transition pedagogy to scaffold and to enhance the first year student learning experience in Australian higher education: Final report*. ALTC Senior Fellowship. Retrieved April 14, 2015 from http://www.altc.edu.au/resource-transition-pedagogy-report-qut-2009

Kift, S., Nelson, K., & Clarke, J. (2010). Transition pedagogy: A third generation approach to FYE - A case study of policy and practice for the higher education sector. *The International Journal of the First Year in Higher Education*, 1(1), 1-20.

Koshy, P. (2014). Student equity performance in Australian higher education: 2007 to 2012. National Centre for Student Equity in Higher Education (NCSEHE), Perth: Curtin University.

Laurillard, D. (2002). *Rethinking university teaching: A framework for the effective use of learning technologies*. London: Routledge-Falmer.

Lockyer, L., & Dawson, S. (2012). Where learning analytics meets learning design. *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge (LAK '12), Vancouver, British Columbia, Canada.* doi: 10.1145/2330601.2330609

Long, P., & Siemens, G. (2011). Penetrating the fog: Analytics in learning and education. EDUCAUSE Review, 46(4). Retrieved 14 June, 2013 from http://www.educause.edu/ero/article/penetrating-fog-analytics-learning-and-education

Macfadyen, L., & Dawson, S. (2010). Mining LMS data to develop an 'early warning system' for educators: A proof of concept. *Computers & Education*, 54(2), 588-599.

Macfadyen, L., and Dawson, S. 2012. Numbers are not enough. Why e-Learning Analytics Failed to inform an Institutional strategic plan. *Educational Technology and Society*, 15(3), 149-163.

Mirriahi, N., & Dawson, S. (2013). The pairing of lecture recording data with assessment scores: A method of discovering pedagogical impact. *Proceedings of the 3rd International Conference on Learning Analytics and Knowledge (LAK '13),* Leuven, Belgium. doi:10.1145/2460296.2460331

Mirriahi, N., Gašević, D., Long, P., & Dawson, S. (2014). Scientometrics as an important tool for the growth of the field of learning analytics. *Journal of Learning Analytics*, 1(2), 1-4.

Nelson, K., Clarke, J., Stoodley, I., & Creagh, T. (2014). *Establishing a framework for transforming student engagement, success and retention in higher education institutions*. Final Report 2014, Canberra, Australia: Australian Government Office for Learning & Teaching.

Nelson, K., Kift, S., & Clarke, J. (2012). A transition pedagogy for student engagement and first-year learning, success and retention. In I. Solomonides, A. Reid & P. Petocz (Eds.) *Engaging with learning in higher education*. Faringdon, UK: Libri Publishing.

Norris, D., Baer, L. & Offerman, M. (2009). A national agenda for action analytics. *National Symposium on Action Analytics*, St. Paul, MN. Retrieved May 12, 2015 from http://lindabaer.efoliomn.com/uploads/settinganationalagendaforactionanalytics101509.pdf

Norris, D., & Baer, L. (2012). A toolkit for building organizational capacity for analytics. Washington, DC: Strategic Initiatives, Inc. Retrieved 12 May, 2015 from https://docs.google.com/a/student.rmit.edu.au/file/d/0B0CqeHHcp-YzMEZPY2hCRHpyLVU/edit

Norris, D., & Baer, L. (2013). Building organizational capacity for analytics. Boulder, CO: Educause. Retrieved 10 May, 2015 from https://net.educause.edu/ir/library/pdf/PUB9012.pdf

Ochoa, X., Suthers, D., Verbert, K., & Duval, E. (2014). Analysis and reflections on the third Learning Analytics and Knowledge Conference (LAK 2013). *Journal of Learning Analytics*, 1(2), 5-22.

Papamitsiou, Z., Terzis, V., Economides, A. (2014). Temporal learning analytics for computer based testing. *Proceedings of the 4th International Conference on Learning Analytics and Knowledge (LAK '14)*, Indianapolis, IN, USA. doi:10.1145/2567574.2567609

Pechenkina, E & Anderson, I (2011) Background paper on Indigenous Australian higher education: trends, initiatives and policy implications. Retrieved May 12, 2015 from www.innovation.gov.au/HigherEducation/IndigenousHigherEducation/ReviewOfIndigenousHigherEducation/Pages/Research.aspx.

Pitman, T., & Koshy, P. (2014). *A framework for measuring equity performance in Australian higher education: Draft framework document v1.6*. National Centre for Student Equity in Higher Education (NCSEHE), Perth: Curtin University. https://www.ncsehe.edu.au/wp-content/uploads/2014/11/Draft_Equity_Performance_Framework_Report_V1.6.pdf

Raca, M., Tormey, R., & Dillenbourg, P. (2014). Sleeper's lag: A study on motion and attention. *Proceedings of the 4th International Conference on Learning Analytics and Knowledge (LAK '14)*, Indianapolis, IN, USA. doi:10.1145/2567574.2567581

Rivera, J., and Rice, M. (2002). A comparison of student outcomes & satisfaction between traditional & web based course offerings. *Online Journal of Distance Learning Administration*, 5(3).

Romero, C., & Ventura, S. (2010). Educational data mining: A review of the state-of-the-art. *IEEE Transaction on Systems, Man, and Cybernetics, Part C: Applications and Reviews,* 40(6), 601-618.

Siemens, G., Dawson, S., & Lynch, G. (2013). *Improving the productivity of the higher education sector: policy and strategy for systems-level deployment of learning analytics*. Society for Learning Analytics Research/Australian Government Office for Learning and Teaching. Retrieved 14 April, 2014 from http://www.itl.usyd.edu.au/projects/SoLAR_Report_2014.pdf

Siemens, G. (2013). Learning analytics: The emergence of a discipline, *American Behavioural Scientist*, 57, 10, 1380-1400.

Siemens G. (2012). Learning analytics: Envisioning a research discipline and a domain of practice, *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge (LAK '12), Vancouver, British Columbia, Canada.* http://learninganalytics.net/LAK_12_keynote_Siemens.pdf

Suthers, D., & Verbert, K. (2013). Learning analytics as a "middle space." *Proceedings of the 3rd International Conference on Learning Analytics and Knowledge (LAK '13),* Leuven, Belgium. doi:10.1145/2460296.2460298

The Australian (2014). *University student attrition rates across Australia*. Retrieved 12 May 2015 from http://www.theaustralian.com.au/higher-education/university-rankings/table-showing-student-attrition-at-australian-universities/story-fna15id1-1226851659938

Thomas, L. (2002).Widening participation in post-compulsory education. *Education & Training*, 44(4/5), 241 – 242. doi:10.1108/et.2002.44.4_5.241.2

Tinto, V. (2009) Taking student retention seriously: rethinking the first year of university. *ALTC FYE Curriculum Design Symposium*, Queensland University of Technology, Brisbane, Australia. Retrieved May 8, 2015 from http://www.fyecd2009.qut.edu.au/resources/SPE_VincentTinto_5Feb09.pdf

Tsui, J., Lau, J., & Shieh, L. (2014). Septris and SICKO: Implementing and using learning analytics and gamification in medical education. *Educause Learning Initiative*. Retrieved May 10, 2015 from https://net.educause.edu/ir/library/pdf/ELIB1401.pdf

Universities Australia (2013). A smarter Australia: An agenda for Australian higher education 2013-2016. Canberra, ACT: Universities Australia. Retrieved April 21, 2015 from https://www.universitiesaustralia.edu.au/news/policy-papers/Universities-Australia-Policy-Statement-2013---2016#.VVFLwPmqpBc

van Barneveld, A., Arnold, K., & Campbell, J. (2012). Analytics in higher education: Establishing a common language. *Educause Learning Initiative*. Retrieved May 10, 2015 from http://net.educause.edu/ir/library/pdf/eli3026.pdf

Van Harmelen, M., & Workman, D. (2012). Analytics for learning and teaching. *JISC CETIS Analytics Series, Analytics for Learning and Teaching,* 1(3). Retrieved May 12, 2015 from http://publications.cetis.ac.uk/wp-content/uploads/2012/11/Analytics-for-Learning-and-Teaching-Vol1-No3.pdf

Verbert, K., Govaerts, S., Duval, E., Santos, J., Assche, F., Parra, G., & Klerkx, J. (2013). Learning dashboards: an overview and future research opportunities. *Personal and Ubiquitous Computing*, 18(6), 1499 – 1514.

Willcoxson, L., Manning, M., Hibbins, R., Joy, S., Thomas, J., Girardi, A., Leask, B., Sidoryn, T., Cotter, J., Kavanagh, M., Troedson, D., & Lynch, B. (2011). *The whole of university experience: Retention, attrition, learning and personal support interventions during undergraduate business studies*. Surrey Hills, NSW: Australian Learning and Teaching Council. Retrieved May 10, 2015 from http://eprints.usq.edu.au/20138/

Wolff, A., Zdrahal, Z., Nikolov, A., & Pantucek, M. (2013). Improving retention: Predicting at-risk students by analysing clicking behaviour in a virtual learning environment. *Proceedings of the 3rd International Conference on Learning Analytics and Knowledge (LAK '13),* Leuven, Belgium. doi:10.1145/2460296.2460324

Zaïane, O. (2001). Web usage mining for a better web-based learning environment. *Proceedings 4th IASTED International Conference on Advanced Technology for Education (CATE '01)*, Banff, Canada. Retrieved 12 May, 2015 from http://webdocs.cs.ualberta.ca/~zaiane/postscript/CATE2001.pdf