ISSN 2382-5855
Advances in Scholarship of Teaching and Learning, Vol.3, No.1, 2016.

THE POTENTIAL OF LEARNING ANALYTICS TO SYSTEMATICALLY ADDRESS DIVERSE LEARNING NEEDS AND IMPROVE STUDENT RETENTION IN AUSTRALIAN HIGHER EDUCATION

Henk HUIJSER
Xi'an Jiaotong-Liverpool University, China & Batchelor Institute, Australia

Deborah WEST
Charles Darwin University, Australia

David HEATH
Charles Darwin University, Australia

This paper reports on partial findings of an Australian Office for Learning and Teaching funded project entitled Learning Analytics: Assisting Universities with Student Retention*. The potential of learning analytics to address diverse learning needs in a systematic and responsive manner is discussed, focusing on how the use of learning analytics can assist in developing responsive and student-centred curricula, and by extension improve student retention. Potential uses of learning analytics to address diverse learning needs and improve retention are explored, as is current use by academics. The paper first provides a literature review with a focus on the potential impact of learning analytics on student retention, and student success and engagement, before reporting on academic-level qualitative data of the project. These qualitative data for this paper are retrieved from a combination of surveys and focused interviews with academics across the Australian higher education sector. The key findings indicate that learning analytics is currently still a potential source of confusion for many academics, that institutional context is a crucial factor, and that a need exists for proactive communication about learning analytics planning and strategy by institutional leaders.*

Keywords: *Learning analytics, student-centred learning, student retention, higher education*

INTRODUCTION

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 optimising learning and the environments in which it occurs" (Siemens & Long, 2011), and has gained great interest in the global higher education space in recent times. In the Australian context, the interest in learning analytics is largely reflective of future potential, rather than generalised or scalable success at this point.

Australia has a relatively well-resourced, sophisticated and mature higher education sector, with a strong commitment to the scholarship of learning and teaching (Universities Australia, 2013). However, an increasing range of choices around technology and data presents challenges as much as opportunities (Hanna, 2000; Verbert et al., 2013). This refers both to technologies themselves (e.g., in the form of choices in data analysis tools) and to the data in terms of the sheer volume of available data (e.g., learning analytics data). In addition, it refers to the skills and knowledge required to take advantage of the opportunities. At present, the higher education sector is wrestling with how to balance attempts to take advantage of all that technology and data analysis have to offer against maintaining a realistic set of boundaries, which give clarity of purpose and promote productivity.

In this paper, we report on partial findings of an Australian Office for Learning and Teaching funded project entitled *Learning Analytics: Assisting Universities with Student Retention* (West et al., 2013). Using the findings from this study, we discuss the potential of learning analytics to address diverse learning needs in a systematic and responsive manner, focusing on how the use of learning analytics can assist in developing responsive and student-centred curricula, and by extension improve student retention. This study aimed to find out how different stakeholders in Australian universities viewed the potential of learning analytics in this respect. The overall project included institutional-level and academic-level surveys and interviews. In this paper, we focus on the academic-level qualitative data of the study, which was drawn from a combination of surveys and interviews with academics across the Australian higher education sector to explore their use (or opinions) of learning analytics in relation to curriculum development and student retention. The data from the institutional-level surveys and interviews, which focused on the opinions of senior management and administrators, will be reported on elsewhere.

For this project, learning analytics was investigated in relation to student retention. Across multiple levels (e.g., political, institutional and academic), student success and retention are crucial aspirations in the Australian higher education context (Bradley, Noonan, Nugent & Scales, 2008). More specifically, improving the participation and success rates of Aboriginal and Torres Strait Islander people (Behrendt, Larkin, Griew & Kelly, 2012; Universities Australia, 2013), people from regional areas and people of low socio-economic status (SES) are important goals (Universities Australia, 2013).

In 2014, the average attrition rate for universities in Australia was 12.82 per cent (*The Australian*, 2014), ranging from 27.26 per cent at the high end to 5.16 per cent at the low end. This has a major impact in a higher education sector characterised by large increases in student numbers, increasing student diversity and changing modes of delivery over the last 15 years. Clarke, Nelson and Stoodley (2013) referred to this development as “stress on institutions to maintain or increase student engagement, success and retention in the midst of increasing cohort mass and diversity” (p. 91). This study set out to explore how learning analytics could be leveraged to assist with maintaining and increasing student engagement, success and retention. While institutional leadership is crucial in relation to a number of institutional factors when it comes to the implementation of learning analytics, academics work directly with students at the teaching level, and, hence, this is where we focus our attention in this paper. The goals of the study were twofold:

1. Identifying the potential uses of learning analytics in addressing diverse learning needs and improving student retention
2. Exploring current use of learning analytics by academics, and how they view the opportunities that learning analytics provide

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 bring (Baker & Yacef, 2009; Campbell, Oblinger & DeBlois, 2007; Dawson, Tan & McWilliam, 2011; Fiaidhi, 2014; Norris & Baer, 2013; Raca, Tormey & Dillenbourg, 2014). 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, Norris, Duin & Brodnick, 2013; Chatti, Dyckhoff, Schroeder & Thüs, 2012). Additionally, learning analytics presents new avenues for addressing ongoing themes such as the effectiveness of particular teaching styles (Baron & Harris, 2012), approaches like gamification (Camilleri, de Freitas, Montebello & McDonagh-Smith, 2013; Holman, Aguilar & Fishman, 2013; Tsui, Lau, J., & Shieh, 2014), or whether the pedagogical intent of teachers is being realised through the learning process (Kennedy et al., 2014; Mirriahi & Dawson, 2013). As noted, this paper explores to what extent academics use learning analytics and how they view the potential. To develop the context for the discussion about the data, however, we will first review the literature as it relates to learning analytics, student retention, and student learning and success.

LEARNING ANALYTICS & STUDENT RETENTION

Learning Analytics

In this section, which is based on the literature, we define learning analytics, discuss the development of learning analytics within a higher education context, and begin to explore practical uses of learning analytics.

To reiterate, Siemens and Long (2011) defined learning analytics as the "measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs". Ferguson (2012) identified two additional assumptions: that learning analytics makes use of pre-existing, machine-readable data, and that its techniques can be used to handle "big data", which is large sets of data that are not practicable to deal with manually.

In addition to the rise of online learning and political concerns (e.g., performance management, metrics and quantification), big data is an important driver in higher education (Clow, 2013; Ferguson, 2012; Johnson, Adams Becker & Hall, 2015), but less well-understood, especially by academics at the teaching "coal face". Gartner Inc. (2015) defined 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.

Ochoa, Suthers, Verbert and Duval (2014) observed that "learning analytics is a new, expanding field that grows at the confluence of learning technologies, educational research, and data science" (p. 5), and they further implied that learning analytics had the potential 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?

This study was mostly interested in analytics that could be applied to the issue of student retention and therefore took a broad view of the definitions.

One practical summary of potential applications of learning analytics is offered on the *Edutech Wiki* (2013):

For individual learners to reflect on their achievements and patterns of behaviour in relation to others:

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

All of these applications have potential follow-up applications to student-retention strategies, because learning analytics can provide data that can help to ascertain elements that contribute to both student retention and/or attrition. These data can then be used in a corrective manner in evaluation exercises. In turn, this is important as student retention is a high priority in the Australian higher education context.

Student Retention

Student retention has become a major focus in the Australian higher education sector over the last 10 years, particularly in response to the *Review of Australian Higher Education*, better known as the "Bradley Review" (Bradley et al., 2008), which 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" (p. xiv). 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 and the highest being 88.8 per cent (Department of Industry, Innovation, Climate Change, Science, Research and Tertiary Education [DIISCCRTE], 2012b).

Furthermore, "by 2020, 20 per cent of undergraduate enrolments in higher education should be students from low socio-economic backgrounds" (Bradley et al., 2008, p. xiv). Students from low socio-economic backgrounds are one of a number of official equity groups, which also include 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, 2012a).

It is acknowledged that there is much work to be done to increase participation of equity students in higher education. For example, 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). Behrendt and her colleagues also recommended ambitious targets: "the panel has recommended that the parity target be set to match retention and completion rates of non-Indigenous students" (p. 10).

One of the great hopes for learning analytics is that it can potentially impact multiple levels across the sector (e.g., political, institutional, and academic levels), and at the institutional level, it can have an impact on different sections of institutions. This creates the opportunity of more holistic approaches to student retention, rather than different sections of higher education institutions implementing measures in isolation. Furthermore, keeping track of progress in terms of student retention requires access to a variety of data, whose reporting often lags significantly behind real time. However, while there is still a lot of emphasis on student retention in the Australian higher education sector, there is also an increasing realisation that student retention may be too narrow a framework, and that instead we should broaden this to a wider concept of student success and student engagement.

Learning Analytics, Student Success and Engagement

It is apparent that student retention is increasingly being subsumed into broader activity and thinking related to student success and student engagement. The question becomes how learning analytics can *specifically* facilitate student retention, progression and completion across the life-cycle, and this relates, firstly, to the First Year Experience (FYE; James, Krause & Jennings, 2010) and, secondly, to the ways in which analytics can be applied to what Kift and colleagues have called “transition pedagogy” (Kift, 2009; Kift, Nelson & Clarke, 2010; Nelson, Kift & Clarke, 2012). This has been particularly important in response to the Bradley Review (Bradley et al., 2008), which in turn is part of a broader agenda that is sometimes called “widening participation” (Chowdry, Crawford, Dearden, Goodman & Vignoles, 2012; Thomas, 2002). 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 student retention are complex and varied (Clarke, Nelson & Stoodley, 2013). Studies have also shown that online courses have higher attrition rates than traditional face-to-face classrooms (Diaz, 2000). There are conflicting results among studies as to which factor has the biggest impact on student dropout rates (Dekker, Pechenizkiy & Vleeshouwers, 2009; Diaz, 2000; Rivera & Rice, 2002). Possible factors include differences in the student demographic as more students from lower socio-economic backgrounds with less formal educational qualifications tend to be enrolled in online courses. Effective use of technologies, time constraints and academic “preparedness” are other impact factors.

Thinking more holistically, Tinto (2009) suggested that to be serious about student retention, universities need to recognise that the roots of student attrition lie not only in students and the situations they face, but also in the very character of the educational settings in which students are asked to learn. If we return to the learning analytics definitions of “measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising 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, p. 3) identified four conditions of student success: expectations, support, feedback and involvement (or engagement). Clarke, Nelson and Stoodley (2013, p. 96) took this idea further and added more details in their Student Engagement Success and Retention Model (SESR-MM) by including the following categories:

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

Both Tinto's four conditions and especially Clarke et al.'s categories are potentially measurable, which is where learning analytics becomes particularly relevant for learning analytics provides the potential to provide the data to measure and analyse each of these categories across whole institutions. Such analyses can then become an integral part of reflection and continuous improvement exercises with a particular focus on student success, and by extension student retention. We will now turn to our study and first discuss our method.

METHOD

Overall, the study employed a mixed-method design featuring four distinct data collection and analysis processes:

1. institution-level survey
2. academic-level survey
3. interviews
4. case studies

The implementation of the mixed-method approach was guided by the work of Greene, Caracelli and Graham (1989), who observed a range of purposes for utilising a mixed-method design. In the context of this paper, one of these is primarily relevant. This is the *development* purpose, which is focused on sequential application of different research methods where one informs the other, in turn. In this case, the institution-level survey deliberately preceded the academic-level survey. As the study was largely exploratory, it was difficult to know what questions would be of most relevance to academic staff without first gaining a sense of how institutions were progressing with learning analytics. The same approach was applied to the development of the interview schedule. Once the academic-level survey data collection had been completed, the analysis revealed themes and questions that the research team wanted to further investigate using a more qualitative approach and thus the interview phase was implemented. As mentioned, in this paper, we focus on the academic-level survey and academic-level interviews only.

Academic-level Survey

The academic-level survey was conducted between September and November of 2014, was targeted at academic staff (e.g., teachers, student support and/or academic developers), and was focused on what they thought about learning analytics and/or how they were using learning analytics in the context of student retention. The survey employed a purposive, snowball sampling strategy to recruit self-selecting individuals (*n*=353). Of the respondents, 276 were academics involved in teaching students.

The sample was purposive in the sense that invitations to participate were distributed in settings where the target audience of academics were located (most commonly via university staff email lists). It was self-selecting in the sense that academics receiving the invitation could then make their own free choice about whether to participate with the help of relevant guidance in a project information sheet. It was a snowball sample in the sense that the research team both distributed invitations themselves and invited colleagues in their professional networks to also forward the invitation through their own academic networks.

Responses were kept anonymous. To minimise risk of multiple completions by individuals, the survey software used for this study only allowed one survey attempt per computer or IP address. Participants could save and return to an incomplete survey anytime they wished. After two inactive weeks, an in-progress attempt was automatically closed and placed with completed surveys.

Academic-level Interviews

A series of semi-structured interviews were conducted between December 2014 and February 2015 with self-selecting respondents who had completed the academic-level survey. This consisted of 23 people from 15 different universities. Respondents held a variety of roles (e.g., teacher, educational developer, student support officer, librarian, learning analytics project leader, tutor, and learning and teaching leader) and spanned different academic levels. The purpose of the interviews was to expand the narratives around some of the more interesting themes uncovered in the more quantitative aspects of the study, for example, where respondents involved with various aspects of learning analytics were positioned in the organisational structure, or what elements of learning analytics the majority of respondents were familiar with. Each interview was digitally recorded (audio) and then transcribed verbatim for coding. The data were manually anonymised (e.g., roles and institution names were removed).

In terms of the "structured" aspect of the interviews, the five primary interview questions were:

1. What is learning analytics to you?
2. What do you think learning analytics can be used for?
3. What is your institution currently doing around learning analytics?
4. What do you currently do in your teaching or work role that you see as directly related to student retention and/or success?
5. Do you have any other comments?

FINDINGS AND DISCUSSION

One of the features of the overall mixed-method design was that it facilitated the triangulation of data and identification of key messages that spanned different pieces of data. Data analysis revealed a number of headline findings, which came through multiple data sources that were both quantitative and qualitative and included institutional-level and academic-level surveys and interviews, as well as an extensive literature review:

1. The higher education sector in Australia is at an early stage of development, implementation and understanding of learning analytics
2. Context is critical and underpins the development, implementation and use of learning analytics for student retention
3. Tensions exist around the extent to which learning analytics can drive actions and behaviours or can take the functions of people
4. Tensions exist between "business" needs, wants and limitations (e.g., costs) and "educational" needs and wants (e.g., academic freedom and innovation in learning and teaching)
5. People across institutions have a key role to play in leveraging the opportunities of learning analytics which must take account of the relationships between strategy, planning, policy and action
6. Establishing relevant business and educational questions is critical

The following subsections explore each of the headline findings and illustrate how the data contributes to each of these findings.

Learning Analytics Is at an Early Stage of Development in Higher Education

Understandings about how learning analytics could be implemented and leveraged towards student retention were quite limited. For the most part learning analytics activity is concentrated centrally (in business intelligence and learning analytics projects and pilots). In other words, it is currently concentrated in isolated pockets where individual organisational units have a direct stake in it, rather than holistically linked across institutions. This means that at the academic level (teachers, etc.), learning analytics are often not a daily, weekly or even monthly topic of conversation with different colleagues, as Table 1 shows.

Table 1

*Absolute Frequency with which Academic-level Survey Respondents Engage in Learning Analytics Discussions with Selected Groups (*n *varies by variable)*

Group	Approx. daily	Approx. weekly	Approx. fortnightly	Less than monthly	Approx. monthly	Never
Teaching Staff (*n*=319)	7	27	24	45	115	101
Programme or Course Co-ordinator (*n*=304)	5	17	15	38	84	145
School or Faculty Management (*n*=306)	3	6	4	33	103	157
Learning Support Staff (*n*=305)	9	16	18	34	74	154
Students (*n*=307)	3	14	12	19	77	182
Colleagues in Communities of Practice (*n*=306)	5	19	15	33	68	166
Central L&T Group Staff (*n*=302)	12	14	11	22	73	170
Student Support Staff (*n*=296)	5	8	10	24	71	178
Institutional Management (*n*=299)	3	11	4	21	58	202

Whilst the study found that the Australian higher education sector is in its early days when it comes to the development, application and use of learning analytics, data from the different sources (i.e., institutional-level and academic-level surveys and interviews) help clarify what that actually means in more specific terms. This is reflected in the following points that refer to the different stages that various institutions are at:

1. Institutions are actively seeking to understand what learning analytics is and how it might be leveraged at their institution
2. Institutions are aware that getting their data infrastructure better integrated is probably going to be helpful, even if they are not yet completely sure how
3. Most institutions have developed some analytics capacity and experience through centralised business intelligence projects
4. Many institutions are currently running learning analytics pilot projects to explore ways of applying learning analytics and/or testing different learning analytics tools, for example, applications within Blackboard Analytics
5. The technical and multi-faceted nature of working with integrated data and advanced learning analytics means that planned projects often take longer than anticipated or hit roadblocks
6. Generalisable, scalable successes remain elusive for now, which reflect that many pilot projects have revealed challenges (e.g., inconsistency in grading schemas and nomenclature used by academics) that need to be addressed in order for projects to re-piloted or expanded

Context Is Critical and Underpins the Development, Implementation and Use of Learning Analytics for Student Retention

There appears to be great variability in learning analytics across institutions in the sector, in terms of preparedness, issues of importance, strategic positioning, executive support and resourcing. This was reflected in this study's interview data, which showed significant individual variety between different institutions' contexts, and, more importantly, even within individual institutions (e.g., with academics often having very different levels of awareness about learning analytics than the executive-level staff). Thus, institutional context represents a set of key variables that are important considerations in how learning analytics might be implemented.

Whilst some elements that impact the implementation of learning analytics were common across participating institutions (e.g., the presence of Learning Management Systems [LMSs] such as Moodle or Blackboard, and Student Information Systems [SISs] such as Callista), many more differences were articulated. Amongst participating individuals and institutions there was wide variation in:

1. Restrictions around teaching outside the LMS – Some institutions have a set of approved tools, some do not restrict at all, and some do not allow teaching to take place outside the LMS. This becomes an issue, as the LMS is the primary tool for the collection of learning analytics data.
2. The location and extent of executive sponsorship of learning analytics – This ranges from centralised to de-centralised organisational units, and from academic to IT areas.
3. Prioritisation of student retention as an issue of focus – This is not necessarily the focus for learning analytics development in all institutions as for some universities, student retention is a much more pressing issue than for others (e.g., less wealthy regional universities compared to wealthy research-intensive universities).
4. The types of learning analytics being focused on – Some institutions are pursuing

personalisation, some are pursuing predictive analytics, whilst others are focusing on exploring curriculum and teaching improvement.
5. The types of data that people can access and are interested in exploring – For example, in some institutions, academics have much more extensive access to learning analytics data than in other institutions. In addition, some academics have a specific interest in exploring data related to specific student cohorts (e.g., Indigenous students).
6. Student cohorts with wide variability depending on the institution – For example, research-intensive urban universities tend to have a more homogenous student cohort than smaller regional universities, or universities with large distance-education cohorts.
7. The degree of centralisation of learning analytics – Some institutions are actively involving academic staff in the uses and applications of learning analytics, whereas others are focused on more centrally contained projects, which are managed by non-academic staff from ICT units or by data analysts.

Tensions Exist around the Extent to which Learning Analytics Can Drive Actions and Behaviours, or Replace People

A broad tension was highlighted around the role of people, the role of computers, and the implications for workloads in the process of gathering and responding to learning analytics data. Personal responses to address student needs, using a manual system, were still considered important by institutions. Moreover, a number of staff in the interviews talked about personal approaches (e.g., telephoning students) having increased, rather than declined in recent times. However, at this stage this is likely the result of an increased focus on student-retention interventions, rather than a response to increased access to learning analytics data.

Interview participants identified clear benefits of a balance between manual and automatic responses, as indicated in the following quotes:

> Even though you are using automated systems to communicate and provide feedback, you still have to make sure that it is personalised and meaningful for students and that takes time and consideration.

> Statistics can be helpful, but it can also be useful to talk to students directly and see what they actually think they need themselves.

Tensions Exist between "Business" Needs, Wants and Limitations (e.g., Costs) and "Educational" Needs and Wants (e.g., Academic Freedom, and Innovation in Learning and Teaching)

One clear tension to come out of the interview data related to variability in how learning analytics might be positioned in a university and the role of academics in it. An underlying element of this tension relates to different agendas; for example, a tension between institutional/business needs and limitations on the one hand, and what academics would like on the other, and how these agendas may be satisfied within institutional learning analytics infrastructures. Within this discussion, the idea of centralised versus de-centralised models of managing learning analytics arose, with academics mostly expressing a preference for de-centralised models to allow them to tailor the application of learning analytics to their individual practice and student cohorts.

Overall, there is strong interest in learning analytics amongst academic-level staff. Academics are particularly interested in the following relatively modest or achievable applications:

1. better understanding who is in their class (demographics, prior academic record, etc.)
2. consolidated information about individual students at the touch of a button (e.g., seeing how their students are doing in other units, what their demographic data is, whether they are using resources, all in one place)
3. learning analytics being used for justification of directives relating to their teaching (e.g., when academics are told to respond in 24 hours to students, is there evidence for this being useful?)
4. improving *both* student (e.g., resource access patterns, socialisation) and teacher (e.g., teaching style, unit design) behaviours with respect to learning

Academic staff reported that their institution was not really meeting their needs in ways that would help them get going with learning analytics, which include access to data, interpretation of data, professional development and how the use of learning analytics would affect them. For example, academics reported that they want the freedom to teach how they feel is most appropriate – outside the LMS can be one such case. Yet, this may then mean that potential data is not available for use in learning analytics, which, in turn, means that the available data may be incomplete.

A common view expressed during the interviews, which is also reflected in the literature (Ferguson, 2012), was that students should be at the centre of analytics thinking and that ethical principles should reflect this, which would then have the potential to extend criteria for learning success beyond grades and persistence so as to include motivation, confidence, enjoyment, satisfaction and meeting career goals. The latter was mentioned, in particular, by a number of respondents in the academic-level interviews and a link was drawn to specific cohorts of students (e.g., students from low socio-economic backgrounds and international students). This is probably not surprising as learning analytics was discussed and framed in the context of student retention during the interviews. Expanding student retention towards a broader and more holistic concept of student success could also lead to a move away from summative assessment towards formative assessment. To achieve this will require transparent methods of reporting and visualising analytics that are personalised, can be easily understood by learners and are clearly linked with ways of improving and optimising their learning.

People across Institutions Have a Key Role to Play in Leveraging the Opportunities of Learning Analytics

Even where institutions were largely conducting learning analytics centrally, there was still a crucial role for people across the institution to play, which relates to one of the key requirements of successfully working with large data sets: that data is validated, trustworthy and current. For instance, one institution wanted to work centrally with assessment data across a whole range of courses and units, so they made pieces of early, low-stakes assessment mandatory to facilitate this. Nevertheless, there were still reports of academics not using the LMS to record grades, which affected the ability to utilise the data.

Another example is teaching outside the LMS. This poses a potential problem when it comes to learning analytics in the sense that it makes the data incomplete if the data collected are restricted to institutional systems such as LMSs and SISs. Table 4 shows a range of teaching activities that took place outside of the LMS, often for assessment purposes:

Table 2

*Tools, Utilities and Activities for Teaching outside the LMS (*n*=276 who teach students)*

Variable	Category	Absolute Frequency	Relative Frequency
Tools or utilities outside the LMS used for teaching (*n*=276)	Does not use tools or utilities to teach outside the LMS*	120	44%
	Website hosted externally	57	21%
	Website hosted by their institution	54	20%
	Others	53	20%
	Social media applications	51	19%
	Mobile apps	22	8%
Teaching activities conducted outside the LMS (*n*=156)**	Provision of access to learning materials	89	63%
	Assessment submission and feedback	75	52%
	Learning focused interactions between lecturers and students	59	41%
	Learning focused interactions between students	48	34%

*Notes: *mutually exclusive response*
*** n *excludes participants who do not teach outside the LMS*

Of the 55 per cent of universities who indicated that they do not place any restrictions on the use of external systems, only one had a process to capture any data but without the ability to integrate it with any other data set. Thus, a high level of importance should be placed on designing infrastructure and teaching in ways that will take advantage of learning analytics if this is strategically important.

Establishing Relevant Business and Educational Questions Is Critical

Participants identified an immense variety of data sources and variables that could be of interest. Developing a clear focus on the use of learning analytics is important but the focus is often restricted to infrastructure. However, a clear focus, aided by key targeted questions to be addressed, will assist institutions to develop readily accessible reports for academics with a focus on student success and retention without overloading central services.

Participants in the academic survey were asked what type of data they would like access to. Most of the 150 respondents indicated what they would like to find out about their teaching practice and their students' learning (rather than identifying the data they needed). Furthermore, analysis revealed that while academic-level respondents came from various main roles (teaching staff, learner support, postgraduate research and management), each group identified key targeted questions or areas of focus. This is in line with Kennedy et al.'s (2014) work, which, like our project, has a focus on what they call "returning learning analytics to teachers", which aligns with our focus on academics in this paper. Their work

ISSN 2382-5855
Advances in Scholarship of Teaching and Learning, Vol.3, No.1, 2016.

focused on linking the learning design of online tasks provided to students with the learning analytic affordances of the technology-based tools that support them. The following are some example questions from respondents in our study, categorised into two broad themes:

Improving curriculum/course design and teaching:

1. Is course design effective?
2. Which course(s) are performing well? (within a school, faculty, university)
3. How can I improve my course design and teaching to improve engagement and performance?

Improving student retention and performance:

4. What are the indicators?
5. Who are the most at risk?
6. What interventions are more likely to be effective?
7. What effect does intervention have on students (based on low results observed through analytics)?
8. What trends can we see in terms of at risk students?
9. Are there relationships between progression, enrolment status, performance?

LIMITATIONS

This study has some limitations and resolving these will both help to set the findings in their proper context and to indicate avenues for further work. Firstly, the sample size means that the external validity of the data is relatively limited. However, the authors have taken steps to carefully describe the sampling process and demographics. Secondly, the sample size also impacted the statistical power and the end result is therefore a largely descriptive and exploratory survey based on self-report data.

Some limitations also emerged around the construct validity of the study as evidenced by a number of questions in the survey in which participants expressed that they were unsure what learning analytics was and whether it was available to them and their institution.

However, despite these limitations, the value of the study can be seen as follows:

1. The issues illustrated are relevant and at least locally impactful, even if they are not universal.
2. The mixed-method design means that academic-level survey data can be connected to other project data (e.g., West et al., 2015) in very specific ways (e.g., contradictions and tensions between institutional direction and teachers priorities can be considered using the different data sets).
3. Whilst this project was taking place, other work was occurring (e.g., a University of South Australia led Office for Learning and Teaching project [Dawson et al., in press]) which can help expand the breadth and range of understanding.
4. Currently, research at the sector level seems liable to illustrate further questions rather than solutions to specific problems because key challenges and issues are still being delineated and uncovered through pilot studies and exploration within many institutions.

5. The research team aims to refine and repeat data collection in the near future to provide a longitudinal point of comparison, which might also allow for reliability to be further explored.

CONCLUSIONS

In this paper, we have reported on a study about learning analytics in the Australian higher education context with a specific focus on where academics are at with regards to learning analytics. While we have discussed six overall and interrelated headline findings, three broad conclusions can be drawn from the data presented with reference to academics. Firstly, learning analytics is currently still a potential source of confusion or frustration for many academics. Secondly, institutional context is a crucial factor. Thirdly, until learning analytics is widely established, there is a need for institutional leaders to proactively communicate what they are doing, what they are planning and what is expected of teaching staff around learning analytics. Learning analytics offers much potential to systematically address diverse learning needs and improve student retention. However, a whole-of-institution approach and transparent strategic leadership and communication are required for that potential to be fulfilled.

Acknowledgement

Support for this publication has been provided by the Australian Government Office for Learning and Teaching. The views expressed in this paper do not necessarily reflect the views of the Australian Government Office for Learning and Teaching.

Authors

Dr Henk HUIJSER is an educational developer at Xi'an Jiaotong-Liverpool University, China and an adjunct researcher at Batchelor Institute, Australia. His research interests include technology-enhanced tertiary education, problem-based learning and cultural studies, and he has published widely in all these areas. For more information, please visit: http://henkhuijser.webs.com/researchpublications.htm. Email: henk.huijser@xjtlu.edu.cn

Associate Professor Deborah WEST is Director, Learning and Teaching at Charles Darwin University, Australia. Her current research interests include the use of learning analtyics, online pedagogy and higher education leadership. She has led a wide range of federally funded research projects and has published extensively in relation to learning and teaching as well as in her disciplinary area of social work. Email: deborah.west@cdu.edu.au

David HEATH is a research associate at Charles Darwin University, Australia. He has been a project officer on a range of Australian Research Council and Office for Learning and Teaching (and its predecessors) funded projects, with the latest being the *Learning Analytics: Assisting Universities with Student Retention* project from which this paper was developed. His research interests include learning and teaching, social work and visual design and multimedia. Email: david.heath@cdu.edu.au

REFERENCES

Baer, L., Norris, D., Duin, A., & Brodnick, R. (2013). Crafting transformative strategies for personalized learning/analytics. In *Proceedings of the 3rd International Conference on Learning Analytics and Knowledge (LAK '13)* (pp. 275–277). Leuven, Belgium: ACM International Conference Proceeding Series. 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

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

Behrendt, L., Larkin, S., Griew, R., & Kelly, P. (2012). *Review of higher education and outcomes for Aboriginal and Torres Strait Islander people: Final report*. Canberra, Australia: 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

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

Camilleri, V., de Freitas, S., Montebello, M., & McDonagh-Smith, P. (2013). A case study inside virtual worlds: Use of analytics for immersive spaces. In *Proceedings of the 3rd International Conference on Learning Analytics and Knowledge (LAK '13)* (pp. 230–234). Leuven, Belgium: ACM International Conference Proceeding Series. doi: 10.1145/2460296.2460341

Campbell, J., DeBlois, P., & Oblinger, D. (2007). *Academic analytics: A new tool for an era*. [Presentation slides]. Retrieved May 12, 2015 from https://net.educause.edu/ir/library/pdf/ELIWEB0710.pdf

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

Chowdry, H., Crawford, C., Dearden, L., Goodman, A., & Vignoles, A. (2013). 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. In *Proceedings of the Higher Education Research and Development Society of Australasia Conference, Auckland,* *New Zealand*. Retrieved May 12, 2015 from http://eprints.qut.edu.au/60024/2/60024.pdf

Clow, D. (2013). MOOCs and the funnel of participation. In *Proceedings of the 3rd International Conference on Learning Analytics and Knowledge (LAK '13)* (pp. 185–189). Leuven, Belgium: ACM International Conference Proceeding Series. doi:10.1145/2460296.2460332

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

Dekker, G., Pechenizkiy, M., & Vleeshouwers, J. (2009). Predicting students' drop out: A case study. In *Proceedings of the 2nd International Conference on Educational Data Mining (EDM '09)* (pp. 41–50). 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]. Retrieved May 12, 2015 from http://home.earthlink.net/~davidpdiaz/LTS/pdf_docs/dissertn.pdf

Department of Industry, Innovation, Climate Change, Science, Research and Tertiary Education (DIICCSRTE). (2012a). *2011 full year higher education student statistics Appendix 2 – Equity Groups*. Canberra, Australia: Australian Government. Retrieved June 18, 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). (2012b). *2011 full year higher education student statistics Appendix 4 – attrition, progress and retention*. Canberra, Australia: Australian Government. Retrieved June 14, 2013 from http://www.innovation.gov.au/HigherEducation/HigherEducationStatistics/StatisticsPublications/Pages/2011StudentFullYear.aspx

EduTech Wiki. (2013). *Learning analytics*. Retrieved June 14, 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.

Fiaidhi, J. (2014). The next step for learning analytics. *IT PRO, 16*(5), 4–8. Retrieved May 12, 2015 from https://www.computer.org/csdl/mags/it/2014/05/mit2014050004.pdf

Gartner Inc. (2015). *Big data*. Retrieved May 30, 2015 from http://www.gartner.com/it-glossary/big-data

Greene, J., Caracelli, V., & Graham, W. (1989). Toward a conceptual framework for mixed-method evaluation designs. *Educational Evaluation and Policy Analysis, 11*(3), 255–274.

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. In *Proceedings of the 3rd International Conference on Learning Analytics and Knowledge (LAK '13)* (pp. 260–264). Leuven, Belgium: ACM International Conference Proceeding Series. doi: 10.1145/2460296.2460350

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

Johnson, L., Adams Becker, S., & Hall, C. (2015). *2015 NMC technology outlook for Australian tertiary education: A horizon project regional report*. Austin, TX: The New Media Consortium.

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. In *Proceedings of the Rhetoric and reality: Critical perspectives on educational technology, 31st ascilite Conference* (pp. 436–440). Dunedin, New Zealand: ascilite2014. 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*. Mt Lawley, Western Australia: ALTC Senior Fellowship Program. 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*. Perth, Australia: National Centre for Student Equity in Higher Education (NCSEHE), Curtin University.

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)* (pp. 180–184). Leuven, Belgium: ACM International Conference Proceeding Series. doi: 10.1145/2460296.2460331

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* (pp. 117-144). Faringdon, UK: Libri Publishing.

Norris, D., & Baer, L. (2013). *Building organizational capacity for analytics*. Boulder, CO: Educause. Retrieved May 10, 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.

Raca, M., Tormey, R., & Dillenbourg, P. (2014). Sleeper's lag: A study on motion and attention. In *Proceedings of the 4th International Conference on Learning Analytics and Knowledge (LAK '14)* (pp. 36–43). Indianapolis, IN: ACM International Conference Proceeding Series. doi: 10.1145/2567574.2567581

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

Siemens, G., & Long, P. (2011) Penetrating the fog: Analytics in learning and education. *EDUCAUSE Review, 46*(4). Retrieved May 20, 2013 from http://www.educause.edu/ero/article/penetrating-fog-analytics-learning-and-education

The Australian. (2014). *University student attrition rates across Australia*. Retrieved March 12, 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*. Brisbane, Australia: ALTC FYE Curriculum Design Symposium, Queensland University of Technology. 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, Australia: Author. Retrieved April 21, 2015 frohttps://www.universitiesaustralia.edu.au/news/policy-papers/Universities-AustraliaPolicy-Statement-2013---2016#.VVFLwPmqpBc

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.

West, D., Lizzio, A. Miles, Toohey, D. C. Huijser, H., Bronniman, J., & Searle, B. (2013). *Learning analytics: How it can assist universities with student retention*. Sydney, Australia: Office of Learning and Teaching, Australian Government.

West, D., Huijser, H., Heath, D., Lizzio, A., Miles, C., Toohey, D., Brönnimann, J., & Searle, B. (2015). *Forum resources*. Retrieved September 25, 2015 from http://www.letstalklearninganalytics.edu.au/national-forum