Measuring engagement: an institution-wide implementation of learning analytics to increase retention

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Abstract

To address the ever more complex issues of student engagement, retention and success, CQUniversity has developed and implemented a learning analytics system. The EASI system was implemented in 2014, and by 2016 had been used to facilitate interactions with over 78% of students. As an optional tool for academics, the uptake is indicative of the value of the system and its perceived usefulness by staff. A more compelling metric is student engagement, where heightened Moodle activity is statistically linked to interventions directed from the EASI system. The challenges of EASI's implementation included both design and organisational issues, and have resulted in a number of lessons for other higher education institutions following a similar path. These lessons include a bottom-up approach; working with academics; and considerations of ethics and privacy.

Monitoring engagement in higher education

Students' engagement with their learning and connection to their studies is vital for their success (Kift, 2015). Early intervention is key, and it has been shown that students who do not engage early in their study, particularly in their first year, are less likely to continue and succeed (Wood, Gray-Ganter & Bailey, 2016). Measuring engagement, on the other hand is often difficult (Nelson, Quinn, Marrington & Clarke, 2011). This is particularly so in CQUniversity, as a multi-campus, regional university with a large Distance Education cohort. Students can choose to study face-to-face, online or a combination of both. The learning management system (LMS), Moodle, is a core system and all units are now represented online, and accessed by all students irrespective of study mode. CQUniversity is in a unique position to implement a monitoring and interventions system using learning analytics because of this complex learning environment and heavy reliance on technology.

This paper presents the links between LMS access and success in university study, the implementation of learning analytics to the LMS to analyse student engagement, and the development of an innovative, institution-wide system to support an engagement which influences retention and success.

Learning analytics

Learning analytics is a relatively new field in higher education where data about learners is utilised to better understand learners and the environments in which they learn (Siemens & Baker, 2012). The burgeoning interest in learning analytics is typically directed at the prediction of student success, although some provision for "just in time" interventions is also evident (Lodge, 2011). In the literature, the term learning analytics is also used in conjunction with academic analytics and educational data mining, however the term is generally used to describe the use of data from information systems which are used to improve learning and teaching and much has been written about its potential (Johnson et al., 2013). The literature indicates that learning analytics can contribute to course design, student success, faculty development, predictive modeling, strategic information, student learning needs and reflective practices (Diaz & Brown, 2012; Johnson, Adams Becker, Cummins, & Estrada, 2014). The increasing use of technology in learning and teaching coupled with the ability of the technology to track user interaction, provides unprecedented opportunities for organisations to use this data in novel ways. Two dominant approaches have emerged for which learning analytics is currently being used in higher education (Colvin et al., 2015):

- To aid with the understanding of learners and their learning environments;
- To identify and conduct interventions with students who might be struggling with their studies and to help them succeed.

The potential of learning analytics has lead to a sharp increase in interest in learning analytics as a concept but a quick uptake should not undermine deliberate and mindful implementation (Beer & Jones, 2014). There are few institution-wide learning analytics implementations and there is a lack of experience across much of the sector with the challenges and pitfalls associated with enterprise-wide learning analytics implementation. The major challenge is how to best integrate the tools and processes of learning analytics into the complex practice of learning and teaching (Beer & Jones, 2014; Elias, 2011). In addition, universities are arranged into hierarchical structures based on the function of the staff members (Beer & Lawson, 2015) and can promote overly simplistic approaches to learning analytics (Beer, Jones, & Clark, 2012). For learning analytics to contribute to student retention and success, it requires learning and teaching expertise and experience (Beer et al., 2012; Dawson, 2010). In a traditional university organisational structure, this can be found in faculties or perhaps the central learning and teaching support areas, however for a truly institution-wide implementation, it will have to go beyond these boundaries.

Methodology

This paper is a case study of the development and implementation of a learning analytics system at CQUniversity. The study will trace the development of the system, the issues and problems that occurred, and detail a series of lessons, which can be used by other universities when implementing similar systems. A case study is a valid form of qualitative research, which provides understanding of a situation through thick description (Hamel, 1993). A case study is an ideal method to answer ‘how and why’ questions, especially when there is a contemporary focus within a real life context (Yin, 2013). The underlying philosophical assumptions of the case study are similar to ethnography where the research takes place in a natural setting, striving for a holistic interpretation of a particular event (Hammersley & Atkinson, 1995). The qualitative nature of a case study allows for detailed, holistic understanding of a specific context, rather than a quantitative approach which may only identify a small number of traits in a wider population (Feagin, 1991). In the case of learning analytics implementation at CQUniversity, an illustrative case study is appropriate, serving to make the unfamiliar familiar and to provide common understanding of the topic (Frey, 1992).

Data collection was via participant observation by the designers; self-reports; archival data; and analysis of the learning analytics data. The research question being addressed was: How did CQUniversity develop and implement its learning analytics system, and why was the approach adopted?

CQUniversity’s learning analytics system

During 2009, the Curriculum Design and Development Unit (CDDU) was responsible for maintaining the then Blackboard™ LMS. CDDU was tasked with supporting academic staff with their use of the LMS to deliver online courses. CDDU was also tasked with the institutional support of learning and teaching with a particular focus on improving online learning and teaching practices. As part of this support, CDDU had access to the backend database that was used by Blackboard™ to record student activity. The activity records of tens of thousands of students were analysed to compare student activity within the Blackboard™ LMS and their resulting grades. Figure 1 demonstrates the correlation between student activity within the LMS and their grades.

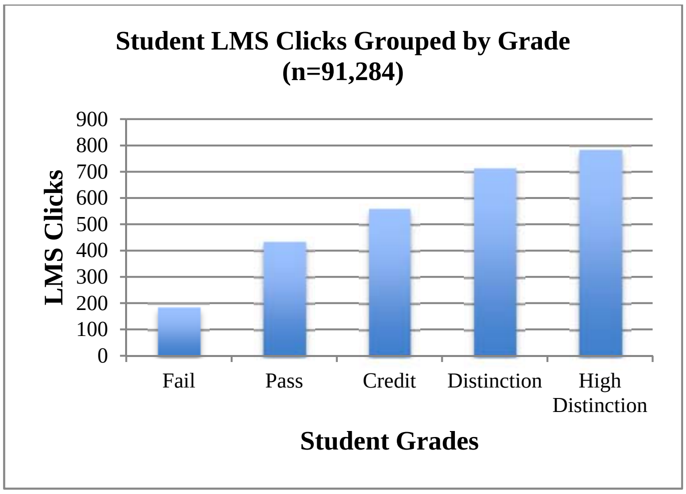

Figure 1: Student clicks by grade on Blackboard™ (2009)

Student success correlated with student activity levels within the Blackboard™ LMS. Staff of CDDU pursued further investigation into these results (Beer & Clark, 2009; Beer, Jones, & Clark, 2009). The results linked LMS activity to an indicator of student engagement, and when the university moved to the Moodle LMS in 2010, there were similar patterns to those found with Blackboard (Beer, 2010; Beer, Clark, & Jones, 2010). (Figure 2).

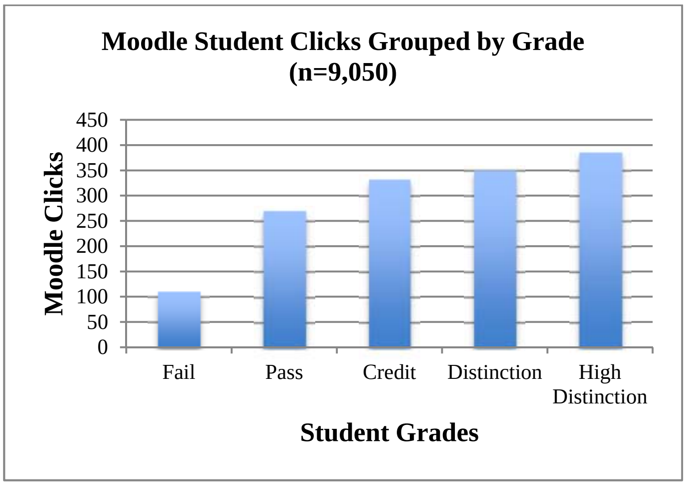

Figure 2: Student clicks by grade on Moodle (2010)

Explorations of other patterns showed correlations between teacher activity within the LMS and student success, which in turn highlighted the critical influence that academic staff have on student engagement in the LMS (Clark, Beer, & Jones, 2010). Investigations focused on how the analytics data could be used to contribute in a more timely manner during term while students were still studying. This was a significantly difficult task due to diverse student populations and variety of pedagogical approaches across the university's various disciplines (Beer et al., 2012). A small trial of a web-based system was conducted that aimed at helping academic staff identify students who had minimal or no activity in the early weeks of term. The trial was based on a number of patterns that were found to correlate with student success. Some of these correlations included:

- LMS activity and grades. On-average the more active students are within the LMS, the better their result.
- LMS forum reads, posts and replies and grades. High achieving students generally make more forum contributions than other students.
- First day of LMS access in a term. Higher achieving students most often accessed the LMS earlier than other students.
- Gaps in LMS activity across term. Students with whole weeks of little or no LMS activity correlated with lower grades.
- Number of words and question marks in forum contributions. Higher achieving students tended to ask more questions and make more frequent forum contributions than the lower achieving students.

The trial was in part stimulated by anecdotal reports that academic staff needed to quickly ascertain student inactivity in near real-time so as to conduct some sort of intervention to re-engage these students. The web-based system was developed to address this based on the correlations that were being extracted (Figure 3).

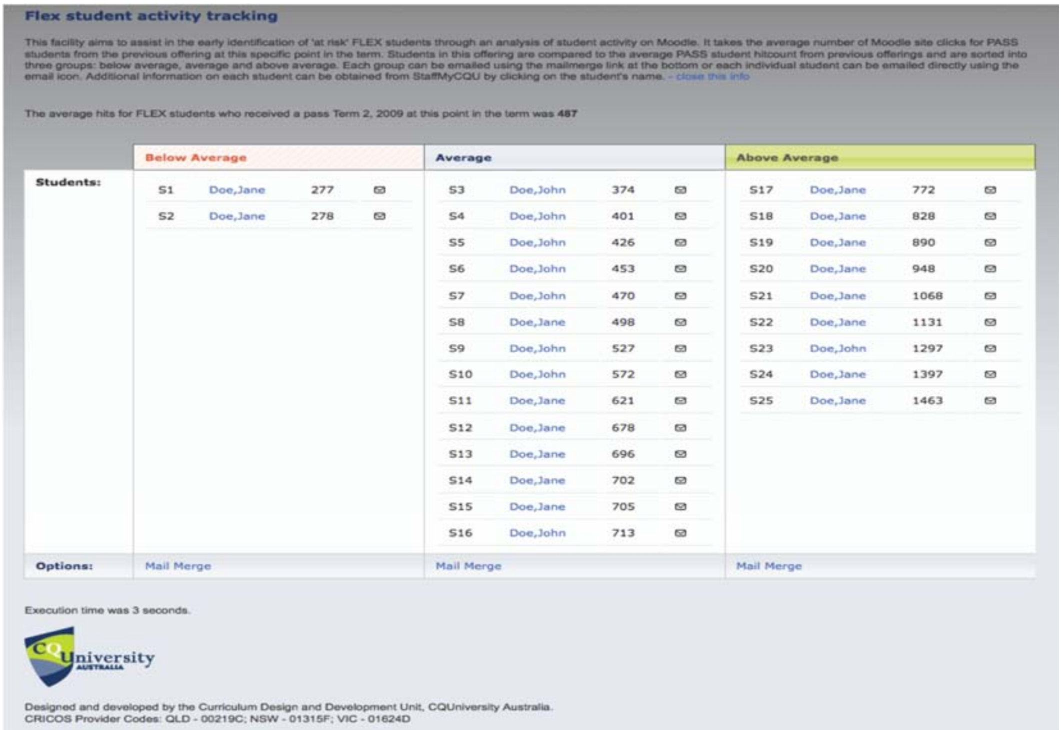

Figure 3: A screen shot of the first 'at risk' student system

The system was designed to couple the representation of student Moodle activity with the ability for academic staff to email students based on their evaluation of student Moodle activity. Academic staff reported how useful it was to see a snap-shot of student activity and be able to act upon the information. Other feedback from academic staff suggested that it was important to be able to situate the students' current level of Moodle activity with each student's academic record for a more reliable interpretation of risk. For example, a high GPA student who had very little activity in any particular week, was not likely to present a high risk of failure compared to a low GPA student. The system designers added academic history to the system in addition to a real-time, automatically calculated risk coefficient known as estimate of success (EOS). Using this information provided, the academics in the pilot contacted students who the system suggested might be struggling. Staff reported that the outcomes of these basic interventions were positive. A larger pilot was conducted with a number of units across different disciplines. This gave the designers valuable insight into what information academic staff needed to help with student success across a variety of disciplines and pedagogies.

During 2013, limited funding was secured to expand the system university-wide, with a focus on improving the university's student retention numbers. Due to the funding limitations, designers developed the databases and software themselves. This was serendipitous in hindsight as it allowed for a bespoke system where the designers' IT and academic knowledge could be combined. The system was built by academics for academics, meaning only the functions that were required were included and the designers were also academics who would be using the system. A unit-based (individual class offering) system was designed that enabled the coordinators of each unit to monitor student performance and activity, and to intervene, as they deemed necessary.

The system was released university-wide for Term 1, 2014 and vast amounts of feedback ensured it addressed issues such as scalability, adaptability and usability. The system became known as the Early Alert Student Indicators (EASI) and constitutes a separate web page available via a link in every Moodle unit site (Figure 4). It includes an estimate of success (EOS) automatically calculated using a proprietary algorithm and an academic can customise the columns shown.

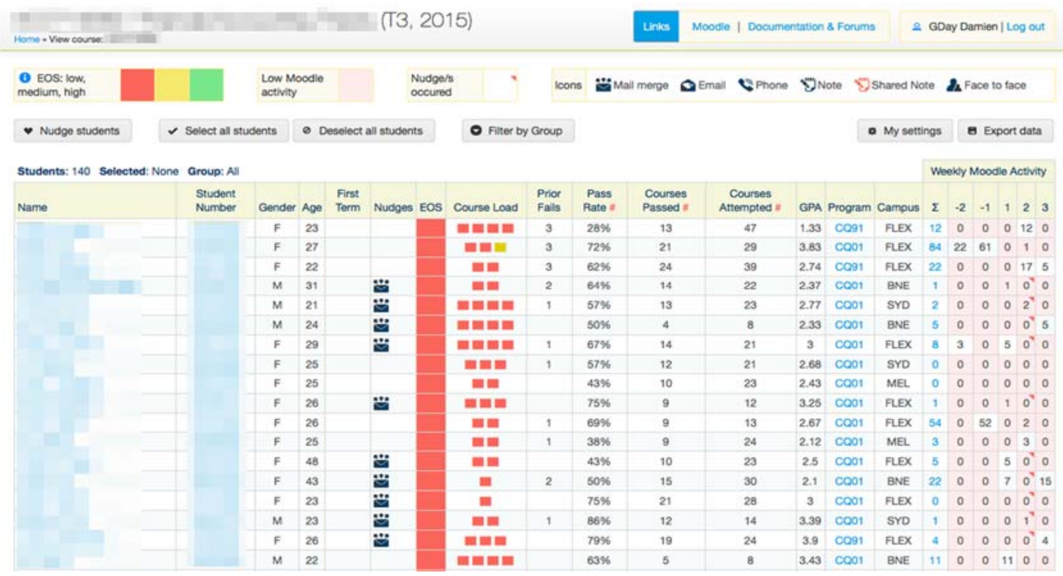

Figure 4: A screen shot of the EASI dashboard

EASI uses the concept of ‘nudges’, which are small prompts designed to re-engage students whose attention might be waning. Teaching staff can select one or multiple students and nudge them in one step thus saving time. The most commonly used of all the available nudge mediums is the mail-merge nudge, with the academic selection student based on a desired criteria such as students who have little or no Moodle activity during the term (Figure 5). Other nudge mediums include phone calls and personal (one-on-one) emails, or otherwise, simple notes or shared notes about one or more students. A key feature of shared notes is that the information recorded is shared with all academic staff teaching the selected students in the same term within their own EASI unit view.

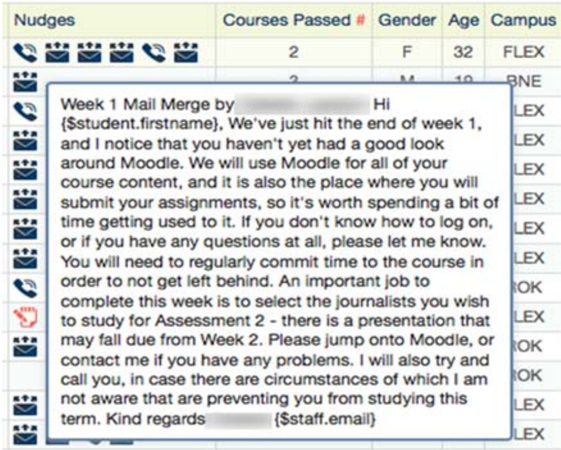

Figure 5: Example of a mail-merge nudge

Benefits of the EASI Learning Analytics system

Uptake and usage

In the period from 1st March, 2014 to 16th May, 2016, EASI was viewed 33,896 times by over 3,900 individual academic staff including program heads, unit coordinators, lecturers and tutors. During this time, EASI facilitated 353,444 nudges to 25,734 students. This has meant that over 79% of all CQUniversity students during this period received a nudge facilitated by the EASI system. The uptake and usage can be attributed to the perceived usefulness and ease of use of the system.

Link to engagement and retention

An unpublished statistical analysis conducted in 2015, examined student Moodle activity before and after an EASI nudge. This analysis compared the activity of students in Moodle who received a mail-merge nudge for the purposes of re-engagement, and at the same time, those that did not as a control. Students sent these nudges had a mean increase of 30 clicks within Moodle compared with four clicks for the control group. The increase in clicks had high statistical significance (two tailed independent samples t test: $t = 11.8$, $df = 132164$, $p < 0.0001$, $n=1396$). This is indicative of an increase in student engagement, since student clicks within Moodle are an indicator of student engagement, or disengagement (Beer et al., 2010). CQUniversity has enjoyed a small increase in student retention of just over one percent since the system started in 2014 (Commonwealth Government of Australia, 2016). Although this increase cannot yet be directly attributable to the EASI system, research is currently being undertaken to establish whether there is a valid link between increased student engagement and student retention.

Return on investment

EASI was developed in-house by a small group of academic staff, for academic staff and was therefore heavily influenced by the academic context. The main expense associated with the development of EASI, was the buyout of staff time. It was estimated that $400,000 was spent on CQUniversiy's enterprise wide learning analytics system that is very well used, is tailored for the CQUniversity context, and is having a positive influence on student engagement.

Challenges of EASI

Assumption of causality

While EASI was being conceived and tested in 2012, the designers were noticing that correlations between student grades and LMS behavior such as those in Figures 1 and 2, while acute and obvious at the aggregate level, were seemingly random and chaotic at the level of the individual student (Beer et al., 2012). This aligned with the notion of complex adaptive systems, whereby apparent disorder at the individual student level coalesces into order at the aggregate levels (Capra & Luisi, 2014; Holland, 2014) and had significant ramifications on the design of EASI .

Interventions within complex adaptive systems can have unanticipated and disproportionate consequences, which limits the predictive potential of retrospective data as it assumes the system, its elements and environment are stable, immovable and do not change (Allen & Boulton, 2011). This is especially pertinent for learning analytics being used for identification and intervention with at risk students due to a range of unknowable factors specific to the individual students (Beer & Lawson, 2015).

The designers considered the learning and teaching environment in which EASI was to be implemented, as a complex adaptive system. As such, the designers focused on providing near real-time representations of the data that academics could use based on their local knowledge of the unit context, rather than comprehensively analysing the predictive value the data may have (Jones, Beer, & Clark, 2013).

Organisational and operational challenges

Learning analytics presents a challenge for universities, and there are currently no established, off-the-shelf approaches, best practices or systems that can be effectively adapted to suit the institutional context. It was proposed that EASI be built in an evolutionary and agile manner. An issue emerged relating to ownership of the development process. EASI was proposed and built by academics within the central learning and teaching support unit rather than in the IT department. The organisation was wary of the risks associated with such an unusual approach to systems development, particularly with the need for ongoing support and maintenance. This challenge was largely overcome through regular collaboration between the designers and IT representatives. The extensive cooperation has resulted in a simple division of responsibility - hardware and operating system infrastructure that hosts EASI is maintained by IT, while the designers remain responsible for the day-to-day operation and support of the EASI application.

Ethical issues associated with the use of student data (Prinsloo & Slade, 2015; Slade & Prinsloo, 2013) emerged during the design and implementation phases of EASI (Lawson, Beer, Rossi, Moore, & Fleming, 2016). While EASI does not collect new data about students, it is representing student information in a way that was not previously available within the university, which can create ethical issues that should be considered systemically throughout the learning analytics lifecycle.

Lessons learned

Lesson 1: Facilitating bottom-up and evolutionary approaches to learning analytics can help organisational learning around the emerging learning analytics concept.

When dealing with the uncertainty and unknowns associated with an emerging, technology-dependent concept like learning analytics, bottom-up and evolutionary approaches can cater for the intricacies associated with contextually specific and complex contexts. This can help the university identify what they require from learning analytics and make informed decisions to the solutions.

Lesson 2: Interdepartmental collaboration and communication are critical for the adoption and implementation of learning analytics.

Organisational structures or silos can limit the potential of learning analytics, which requires the amalgamation of learning, teaching, research and technology. Bridging organisational silos is necessary to overcome overly simplistic, purely technology based conceptions of learning analytics. The benefits of successful cross-institutional approaches must be promoted through senior leadership.

Lesson 3: Promote an approach to learning analytics that biases learning over planning.

The typical approach to technology adoption is via formal, top-down projects based on extensive planning to arrive at a clearly defined future state but can constrain the exploratory approaches that are needed with an emerging concept such as learning analytics. An approach to learning analytics based on learning, rather than planning, can promote more incremental and evolutionary strategies which can better fit the organisational context.

Lesson 4: Do learning analytics with the academics, not to the academics

Academic teachers are likely to have the right blend of local knowledge and proximity to the context for learning analytics to make a strong contribution to student outcomes. They are a valuable source of information and should be key, if not principal stakeholders in any learning analytics endeavour.

Conclusions and future research

This paper introduced the emerging concept of learning analytics in the higher education sector. This context included an extraordinarily complex learning and teaching environment and a growing student retention problem.

In CQUniversity's case, initial exploratory research into learning analytics in 2009 coalesced by 2012 into a formal project aimed at utilising learning analytics to identify students who were at risk of failing. The Early Alert Student Indicators (EASI) system adopted in 2014 is regarded as a successful example of an enterprise-wide learning analytics system. A statistical analysis of EASI has shown a significant correlation between EASI interventions and a corresponding increase in student activity within the Moodle learning management system. This, in turn, is impacting on the retention of the university's student population.

The development of EASI was not without its challenges such as rigid hierarchical structures, cross-institution communication and collaboration along with the shortcomings of typical plan-based approaches to technology adoption. The value to student engagement, retention and success, however, is worth the commitment to overcoming these challenges and it is the aim of future research to show further correlation between these issues and the implementation of real-time monitoring and early intervention strategies. It is also hoped that the lessons learnt here can help other universities who are endeavoring to capitalise on the promise of learning analytics.

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