

Learning Analytics implementations in universities: Towards a model of success, using multiple case studies

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In these pioneering days of Learning Analytics in higher education, universities are pursuing a diverse range of in-house implementation strategies, with varying degrees of success. In this exploratory study we compare and contrast the approaches taken at three demographically different Australian universities. The comparison is made in the context of Delone and McLean's information system success model (1992). In time, a consensus-driven method for using Learning Analytics to improve student learning outcomes will eventuate, including individualized learning, but we are still some distance from this level of maturity. It seems likely that user-friendly proprietary platforms will prosper in the climate of uncertainty. Participants in the study see potential in Learning Analytics but are not sure about how best to realize that potential as the implementation of Learning Analytics systems at Australian universities are still very much in their infancy. Proprietary approaches offering sophisticated functionality seem likely to emerge and take precedence over the trial and error approach. This study addresses an apparent gap in the research as limited studies exist targeting both learning analytics and information system success. The methodology taken explores the research topic through a qualitative lens utilising thematic analysis. The study concludes that digital interventions such as Learning Analytics has great potential to optimize teaching and learning practices. Information systems success research can provide insights into what works and what does not in terms of Learning Analytics implementations. The discipline needs to be systematized for efficient implementation, and must deliver tangible benefits over time.

Keywords: Learning Analytics, Information System Success, Learning and Teaching, Information System Success Model

Introduction

Considering the maturity of Australia's higher education sector, and its demonstrated commitment to the scholarship of teaching and learning, it is perhaps surprising that the tool of Learning Analytics has not played a more pivotal role in providing evidence-based teaching and learning strategies (Universities Australia, 2013). Learning Analytics may be described as the collection, analysis, and reporting of data associated with student learning behaviour (Lockyer, Heathcote and Dawson, 2013). This is not to say that Australian Universities have not been making good use of technology to make the learning and teaching experience more flexible, accessible and engaging, with the overall goal of improving learning outcomes. But full recognition of the potential of Learning Analytics to support more data-driven decisions has not yet been reached. As higher education operates under increasing scrutiny by governments, accrediting agencies and students, new ways to monitor and improve student success will be advantageous. Generally speaking, Australian universities are recognizing the potential of Learning Analytics but given the immaturity of the field and the relatively few successful implementations, there is still something of an experiential vacuum that is impeding progress. Empirical research supports the view that data-driven decisions improve productivity and organizational output, yet for many higher education leaders, it is experience and "gut instinct" that still has greater impact on decisions (Long and Siemens, 2011). As the field of Learning Analytics matures, the focus of theory and practice is moving from post-hoc analysis to the exploration of the possibilities that real-time data can bring (West, et. al, 2015).

What are Learning Analytics?

Throughout the literature, diverse definitions of Learning Analytics can be found (LAK2011; Slade and Prinsloo, 2013; Siemens, 2010; Boyd and Crawford, 2012; Donoghue, Horvath and Lodge, 2019; Lockyer, Heathcote and Dawson, 2013). Emerging from the ongoing discussion has been a degree of consensus for a working definition from the First International Conference on Learning Analytics and Knowledge - "Learning analytics is 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" (LAK2011). (Slade and Prinsloo's (2013) interpretation of the definition is interesting as it includes an ethical angle. They state that Learning Analytics is "the collection, analysis, use and *appropriate* dissemination of student-generated, actionable

data with the purpose of creating appropriate cognitive, administrative, and effective support for learners (Slade and Prinsloo, 2013). Analytics used for teaching and learning decision making and analysis are becoming more important for informing teachers on the success or otherwise of their design of learning experiences and activities, together with the monitoring of student learning for support during the teaching period (Lockyer, Heathcote and Dawson, 2013). Although different definitions exist, most researchers agree that big data, which is often used by analytics, involves large volumes of data gathered by different organizations (Koronios, Gao, and Selle, 2014). Siemens (2010) defines Learning Analytics more specifically involving the use of intelligent data and analytical models to discover connections as well as to predict and advise on learning (Siemens, 2010). Boyd and Crawford (2012) see the term of *big data* as an inaccurate one, as it is less about the data and more about the capability to sift, aggregate and cross-reference useful information buried in large data sets – “Businesses are collecting more data than they know what to do with” (McAfee and Brynjolfsson, 2012, p. 59). This is true for Australian universities (Colvin, et. al, 2016). Donoghue, Horvath and Lodge (2019) describe Learning Analytics as an emerging field that has the purpose of supporting, enhancing, facilitating, predicting and measuring human learning in an educational setting. In a review of the literature on LA, Strang (2016) concludes there is an emphasis on prediction as a reason for employing learning analytics. For the purposes of this study, we used Lockyer, Heathcote and Dawson’s (2013) definition, being the collection, analysis, and reporting of data associated with student learning behaviour. We adopted this definition because it encompasses the original definition from the LAK2011 conference and focuses on student learning.

The outcomes of research into what makes a successful Learning Analytics implementation illuminate issues that are a priority in successful implementations. Knowing this allows for the strategic improvement of teaching and learning outcomes. Considerable variation in students’ manner of engagement with their learning environment (Coates, 2008) has been noted, so it is advisable that the derived analytics be a reflection of their preferred style. If we make the individual student the unit of analysis, we create opportunities for optimisation strategies to be developed tailored to a student’s unique learning style. This inherently inclusive pedagogical approach caters to the learning styles of students with broadly divergent backgrounds, including students with disabilities. Strang (2016) examines a study of students and their engagement with Moodle (LMS). The study presents a snapshot of in time of student learning, however the authors finding report that Learning Analytics in this case was not able to predict student learning performance. This paper examines the Delone and McLean model of Information Systems Success as applied to Learning Analytics systems at three Australian universities. This example of digital intervention is useful to illuminate issues associated with learning and teaching supported by learning analytics. Learning Analytics is an information system. Delone and McLean’s model details a comprehensive framework for assessing the performance of information systems in organizations (Delone and McLean, 2003). Said model is robust, having been applied to information systems across a broad range of types over an extended period. The model will be applied to Learning Analytics in order to find specific areas that Universities can focus on to ensure a successful implementation of the system. The authors are unaware of any earlier instances of Delone and McLean’s model being applied to Learning Analytics, though some preliminary work has been done by Strang (2016) examining the critical success factors involved in Learning Analytics implementations.

Information Systems Success

As stated, we classify Learning Analytics systems as belonging to the broad category known as information systems. By definition, an information system involves gathering, processing, distributing and using information by input, processing and output, with a storage and feedback component (Beynon-Davies, 2013). We argue that Learning analytics can be classified as an information system as it refers to the process of collecting, evaluating, analyzing, and reporting organizational data for the purpose of decision making (Campbell and Oblinger, 2007). Information systems implementations are not known to have a good track record in terms of successful implementations (Nguyen, Nguyen and Cao, 2015). Indeed, it has been noted that a large percentage of information systems implementations are a failure (Beynon-Davies, 2013). The authors consider it appropriate to apply the information systems success literature to the implementation of Learning Analytics systems.

The literature on information systems success is extensive. A key development of the theory of information systems success were authors Delone and McLean (1992). The authors have since updated the theory after contributions from IS scholars to create a better model. The information systems success model has been cited in thousands of papers and has been one of the most influential theories in contemporary information systems research (Nguyen, Nguyen and Cao, 2015). It provides a solid foundation for examining the success or otherwise of Learning Analytics implementation, particularly in relation to the strategic improvement of learning and teaching outcomes.

Delone and McLean performed a systematic review of available published material relating to the success of information systems in organizations.

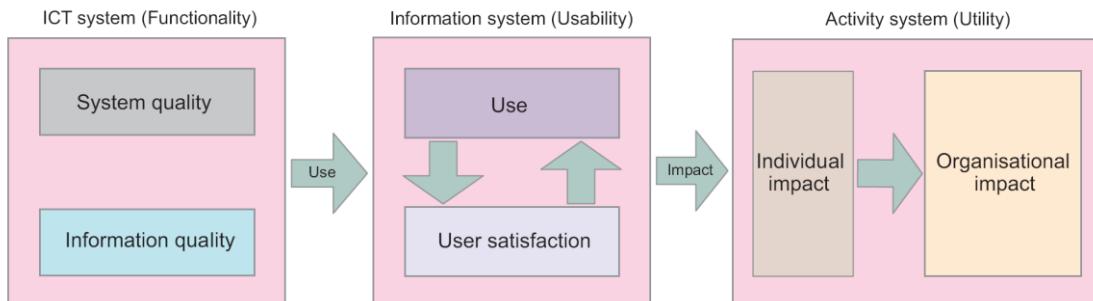


Figure 1: Delone and McLean Model (Delone and McLean, 1992)

There are three main elements to the model. Firstly, the ICT system or Functionality. The system quality focuses on the desired characteristics of the information system whereas the information quality considers the quality of the output from the system. The second element looks at Usability. This element examines how the users interact with the information system in terms of whether the user interface is user friendly and allows them to do what needs to be done. The last element, the Activity system or Utility focuses on the overall impact the information systems has on the individual and the organization as a whole (Nguyen, Nguyen and Cao, 2015; Beynon-Davies, 2013).

The model was updated in 2003 by Delone and McLean and now includes additions such as the intention to use as well as the use and the overall individual and organizational impact being viewed as the net benefits that include user satisfaction and the use of the information system (Nguyen, Nguyen and Cao, 2015) (see Figure 2 below).

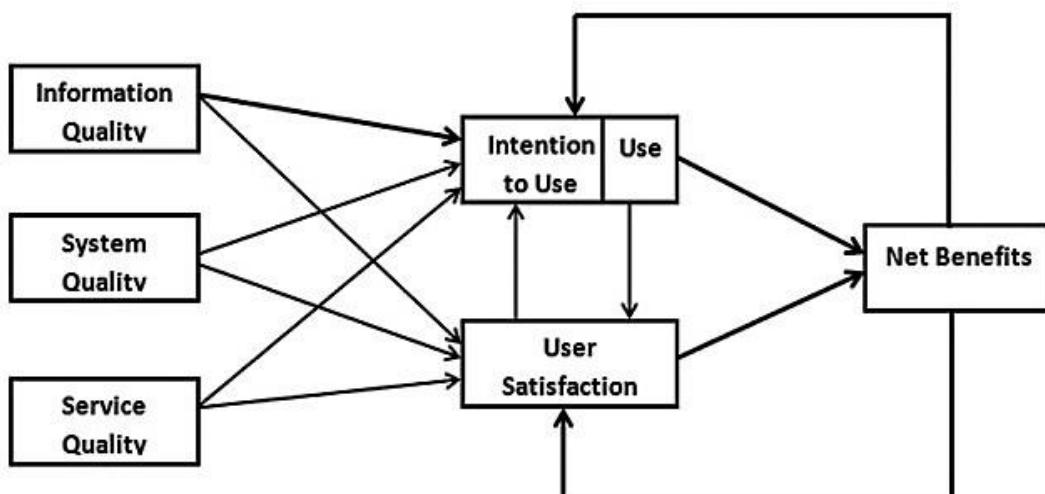


Figure 2: The updated Delone McLean information system success model (Delone and McLean, 2004).

The Delone and McLean model has primarily been used in quantitative studies, but other studies exist that focus on qualitative research. Out of 90 empirical studies outlined in Petter, Delone and McLean (2008) the following qualitative studies were mentioned in Coombs et al, 2001, Scheepers et al, 2006 and Leclercq, 2007. In this project, we put elements of the Delone and McLean model to a qualitative data analysis. In doing so we examine the potential of learning analytics to deliver appropriate functionality and usability to create an information system that delivers actual value to a diverse cohort of students with varying learning styles.

Research Approach

After consideration of the alternatives, the case study approach deemed suitable to the purposes of this project. Researchers have used the case study approach in research across a wide range of disciplines for many years, seeking to understand complex issues. This research aligns with the perspectives associated with the case study approach. Yin (1984) defines case study research as “an empirical inquiry that investigates a contemporary phenomenon within its real-life context; when the boundaries between phenomenon and context are not clearly

evident”; and in which multiple sources of evidence are used (Yin, 1984: 13). Case studies are often used in research because they offer insights that may not be achieved with other approaches (Rowley, 2002). As the generalisability of the case study approach is sometimes questioned, it is best to establish validity using multiple case studies. Multiple case designs are preferred to demonstrate validity. Having multiple cases can be regarded as equivalent to multiple experiments as opposed to having a single case or single experiment (Rowley, 2002). The case study approach is very suitable for exploratory investigations where there is little or no prior knowledge of reality or of a phenomenon (Järvinen, 2001). Performing qualitative research enables the researcher to study events within their real-world context and this includes the relevant culture of the people, organization, or groups being studied. It is crucial that the culture, that is, the unwritten rules and norms governing the social behaviour of groups of people, is considered when conducting this project (Yin, 2011).

Interpretive research has emerged as an important branch in information systems research in recent years (Walsham, 1995). Interpretive research is thought to assist Information Systems researchers in understanding human thought and action in social and organizational contexts. It also has the potential to produce deep insights into information systems phenomena (Klein and Myers, 1999). The research design for this project is an interpretive case study that will be analyzed through qualitative methods. As the interpretivist perspective will be taken, the world will be viewed as a social construction of reality, interpreted and experienced by people and their interactions within the wider social systems in which they exist. According to this research paradigm, the nature of inquiry is interpretive. The intended purpose of the inquiry is to understand a particular phenomenon, not to generalize a population (Antwi and Hamza, 2015).

The foundation of a research study lies with the data collected (Yin, 2011). According to Yin, (2011) data collected in qualitative studies come from four field-based activities: interviewing and conversing; observing; collecting and feeling. This research study adopted the following data collection methods: in-depth interviews, direct observation, and examination of relevant documentation (Yin, 1994).

Data collection and analysis

Data collection began with an approach to the Deputy Vice Chancellors (Research) at each university outlining the project and seeking permission to approach appropriate members of their university community. The DVCs(R) were supportive in their responses. Having obtained approval, key staff were identified at each university. These persons were selected based on their direct involvement with Learning Analytic Systems. In-depth interviews were subsequently conducted with the aforementioned staff at each university. The interview protocols were designed around the key issues derived from an extensive literature review on Learning Analytics around the world (Levy and Ellis, 2006). A documentation review was also conducted around the Learning Analytics policies in place at each university.

It must be noted that this is an exploratory study to establish a benchmark of Learning Analytics practices at representative Australian universities. The Delone and McLean (1994) model was not used to inform the research questions at this stage but will be used in the next phase of the research.

The interviews were recorded and transcribed. The interview data was then coded, and analysis performed using exploratory thematic analysis (Braun and Clarke, 2008). An interpretive approach was taken with the analysis, as the researchers felt it was ideal to represent the perceptions of the staff interviewed about the Learning Analytics system implementations. We acknowledge that Learning Analytics systems are quantitative and therefore measurable in nature, but the subjective impressions that staff have about Learning Analytics are best explored through a qualitative lens for the purposes of this exploratory study.

Case Studies

Data for the Case Study was collected from three demographically diverse Australian universities, two of which were metropolitan, the third being a regional university. The demographic spread of the data sources permit a broadly inclusive view of the Learning Analytics situation in Australian universities.

University One

University One is a public research university servicing low to middle socio-economic areas. A higher than average proportion of its students are first in family, have diverse needs and in some cases have a lower entrance score than those of their immediate counterparts.

University Two

University Two is also a public research-intensive university servicing a middle to high socio-economic demographic. This university is perceived both locally and internationally as prestigious. It routinely attracts students with high entrance scores.

University Three

The third test site is a regional university servicing a large agricultural base, and which has specialized in offering on-line programs for which it has a good reputation. The greatest proportion of total enrolments are online students. These come from widely varying backgrounds, including Low SES, mature aged and professionals seeking career enhancement.

Learning Analytics Implementations

It was immediately clear that each of the data collection sites had adopted different approaches to Learning Analytics. Two used a centralized software suite (though different suites), the third took a course-by-course approach taking account of what information the lecturers wanted from the exercise.

University One

In cooperation with the makers of the Blackboard Learning Management System (LMS), a full-function Learning Analytics Dashboard had been implemented in University One since 2016, beginning with a pilot in that year. The dashboard has since been rolled out and made available to the broader university community. The project was coordinated by the university's Professional Development Department. The dashboard provides a configurable, fine-grained view of student's interactions within the on-line learning environment. This included frequency and duration of access to specific on-line pages. From this it is possible to deduce degree of engagement and a number of other metrics and indicators such as when a student is falling behind with meeting their milestones. Proactive interventions can then be performed via email. One of the challenges with the Dashboard was the volume of data generated and the finding of ways to meaningfully use it.

University Two

University Two established a dedicated Learning Analytics department with the mandate to establish and optimize Learning Analytics as a tool for improving student outcomes. The Tableau[®] software suite is the tool of choice. Tableau[®] draws performance data from every course at the university, monitoring how the course performs in terms of student attendance, engagement with specific course material, student evaluation scores and a range of other metrics. Performance is evaluated through the application of specific performance indicators situated in the within the context of a mature quality framework. Meaning analytics emerging from this quantitative management approach is then used by course conveners to progressively improve the quality of their courses.

University Three

At the third site, a decentralized approach to Learning Analytics was observed. Each course convener has access to a plug-and-play tool-set with which a tailor made Learning Analytics application can be developed. These applications were not necessarily developed from scratch. A range of templates and suggestions provided guidance for conveners. The usefulness of the results across the various implementations varied depending on factors like the lecturer's programming skills, their understanding of what the capabilities of using such a system might be. Usefulness also depended on several other factors including how busy with other matters the convener was.

Analysis

This section presents the analysis that was conducted using exploratory thematic analysis (Braun and Clarke, 2008). The interview data was coded, and analysis used thematic analysis (Yin, 1994). An interpretive perspective was taken in the analysis as the researchers felt it was ideal to represent the perceptions of the staff interviewed about the Learning Analytics system implementations.

Learning Analytics implementations at Universities is still in its infancy

Even though analytics has been used to good effect in business for some time, the use of analytics at universities is in its infancy. In some Australian universities, analytics is the responsibility of their Business Intelligence departments, as in the case of University One. Learning analytics research is closely related to the field of educational data mining. This field has relevance for understanding and optimizing the learning process (Siemens and Baker, 2012) although much of this research has focused on developing predictive models of academic success and retention (Siemens, Dawson, and Lynch, 2014). In another example, University Two, an entire section is devoted to learning analytics, including the business intelligence area and academic analytics, which includes course analytics. University Three is taking a more adhoc approach so there is no formal department or unit devoted to learning analytics.

Defining ‘Learning analytics’

Although some progress has been made, there is as yet no clear consensus on what the term ‘learning analytics’ means (Van Barneveld et al, 2012). Siemens (2013) posits that as the field evolves an authoritative definition will emerge. Perhaps the difficulties in achieving consensus is because Learning Analytics is a relatively new field, or perhaps the reasons are more complex.

It is self-evident that we operate in an increasingly data-driven environment. Analytics can be applied to specific areas like health and safety analytics, or it may apply to an intention, such as learning analytics in relation to improved learning outcomes, and predictive analytics. Or the term may also apply to the object of analysis, for example Twitter analytics, Facebook analytics, Google analytics. Van Barneveld et al (2012) note that higher education’s approach to defining analytics is particularly inconsistent. They found that some definitions were conceptual (what it is) while others were more functional (what it does).

In any event, interested observers use the term in various ways in relation to Learning Analytics. For example, some consider that ‘learning analytics’ *per se* do not exist since no learning takes place with the use of analytics. It is a meta-level pursuit. A professor interviewed from University One views learning analytics as the managing of student behaviour and the promotion of engagement rather than actual ‘learning’ taking place with the use of analytics. The course analytics project at University One utilizes Blackboard and is concerned with mapping students’ engagement behaviour. The system is a meta-level window into their learning. It is not feeding information back to students about their learning. University two takes two perspectives on learning analytics:student facing and academic facing. University three views learning analytics as improving the use of data and evidence to improve learning and teaching outcomes, doing so on a course-by-course basis.

Student facing analytics versus Academic facing analytics

As noted, we see that different Learning Analytics definitions exist but we ask are these definitions talking about the same thing. A finding from the case study interviews was that participants view analytics as either student facing or academic facing. Long and Siemens (2011) introduced the categorisation of learning versus academic’s analytics. Where learning analytics included course-level and departmental analytics as opposed to academic analytics including institutional, regional and national and international analytics. The categorisations were at the objective analysis along with who benefits. In learning analytics, the beneficiaries are learning and faculty whereas the institutional, regional and national and international analytics were at a more systematic level (Long and Siemens, 2011). At University One, student facing analytics is instantiated by feedback to the student about how they are going, for example, are they keeping up with workload/assessment? In this university, the nature of the information in the student facing analytics is distinctly different from that of the staff facing analytics. It is qualitatively different data that poses different challenges in the formulation of meaning by the academic. One academic in the trial commented that there is clearly a lot of potential in this data, but it is not clear how it can be derived. University Two is in the process of building a student dashboard, currently in beta phase in 2019. The beta is being trialled in the medical degree. The choice of student cohort to test the beta upon highlights that different cohorts in different disciplines will probably use the dashboard in distinctly different ways. High achieving medical students’ intent on maintaining high grade point averages (GPA) will use the analytics as a strategic tool to maintain their GPA, whereas students in less-demanding programs will likely use the analytics differently, if at all. The majority of work done at both University One and Two make up this classification of academic facing analytics.

Learning analytics applied to course design

The application of learning analytics to course design was different in the three universities. University One was using Learning Management Systems (LMS) centric models supporting staff making better course management and course design decisions based on a series of dashboards. Although this work is very much in its infancy, based on a one-year pilot implementation. In university one, participants stressed that the first four weeks of any semester is crucial to engaging the student. “*So, how do you capture those students? And modelling who they are and taking note of all the different types they are.*” (University One participant). This university had a process called first assessment; first feedback where those students who did not submit or who failed their first piece of assessment were invited in and staff worked with them to remedy the shortfall. “*Those that picked up the intervention went on to do very well but you would be surprised how many of those were hard to find and some un-contactable or disappeared. And what we concluded was, by week 4 they psychologically dis-enrolled from university*” (University one participant).

University One had also experimented with predictive modelling concerning at-risk students and attrition. It is very easy to diagnose risk at this university, for example it is possible by week 4 of the trimester to determine to an accuracy of 90%, who is going to fail the course, but it is very difficult to act on prevention strategies “*students don't read their email*” University 1 participant). Early intervention is critical. As an interview participant noted “*too often we are very clever at measuring problems rather than presenting potential preventative solutions that don't require analytics but require a lot of common sense, you know, like for example, we can track student's engagement with a course but you know you don't need analytics to tell you that a small piece of early assessment, give them clear feedback and be available for consultation. Good design is still good design and good support and good teaching is still good teaching.*” (University one participant).

University One has created a course analytics system in conjunction with Blackboard. They also have a planned system called Analytics for analytics, which is basically tracking the analytics of engagement. The purpose is to get a supra-level institutional snapshot of engagement in addition to the course level snapshot.

University Two had advanced analytics running on all courses that are offered utilizing the Tableau Tableau® is a proprietary Business Intelligence and Analytics software software. Tableau® is a proprietary Business Intelligence and Analytics software package offering a range of useful functions. On-going risk assessment of every course is performed via this software. The Associate Dean Academic in each school then scrutinises the results. You can take any course and look at the risk factors (scale of 1-3) and see whether the course is at risk in any way. Student evaluation data is also integrated into this system. As an example of a risk factor, declining class numbers (enrolment) are tracked.

Academics at a supervisory level in each school regularly reviews the Tableau® reports to evaluate risk for each school. In an example mentioned during an interview, a course was shown that was not attracting particularly high enrolments at the current semester. Instead of having only intuition to go on, data could be used to determine the root cause of this drop in enrolments. Student evaluations of teaching and learning were loaded into the Tableau® software along with other markers providing data on the current situation. Staff in the Learning Analytics department could drill down into different areas to get more detailed data on all elements of the course.

At University Two, based on examination of previous student behaviour, predictive data analytics was used to interrogate the database and identify patterns. “*You then bring that into the moment and go ok, I now understand the student journey in my course a whole lot better cause I know where they drop off and where they fail. So what I do is put in a series of automated outreach recommenders to those students and then I can use the analytics to monitor the effect of those. I send a recommender to do some more work on getting ready for the assignment and I note that 60% of them pick that up and ran with it. I note that 40% didn't so then I have a triage model and I get my second recommender goes to that 40%*.” (University two participant).

Benefits, Limitations and Challenges of Learning Analytics implementations

Interview participants in the three university case studies were asked about their experiences of learning analytic benefits, limitation and potential challenges. In summary, participants recognized the following benefits from learning analytics:

- Increased data literacy of staff, allowing the formulation of optimization strategies
- Evidence-based practice that generates reliable/usable data
- Data-driven decision making, i.e. quantitative management of student learning

- Observing what enhances learning and what detracts from learning
- De-privatising the classroom which can be an uncomfortable conversation
- Greater accountability on the lecturer and transparency of the conduct of courses
- Improved enhanced student experience of the course
- Quality assurance at the institutional level
- Potential to link artificial intelligence to the analytics to automate/optimize the process.

Regarding limitations, the participants felt that the benefits outweighed the limitations by a big margin. Overall, participants mentioned the cautions of being on the web, for example security issues, would be applied to learning analytic implementations. A major theme across the three university case studies was the idea of uninformed inferences. Educators need to be careful what they infer from learning analytic data (. An interview participant notes that just because a student is logged on to a LMS doesn't mean they are engaged in the course material "*It is like mistaking the leaves for the wind. Measuring the movement of the leaves but the wind is something different.*" The information might be misinterpreted in misleading ways due to not understanding the implications of making uninformed inferences.

In terms of challenges, the issue of technology acceptance and resistance was highlighted amongst participant interviews. "*Staff get caught in the headlights very quickly. Show them a dashboard and they go It is like oh my god. What does all this mean?*" (University one participant).

Using data to support learning is a new way of thinking, one which calls for a new set of skills to look at a set of data and derive useful information from it. The major challenge mentioned by staff at University One is that they are busy and do not have time to look ponder over the data. This would seem to indicate that most of University One's teaching is based on a delivery model rather than a feedback model. Also, at University One, there is not a culture of continuous feedback and improvement. People feel they are time poor and do not see a clear benefit in investing time and effort in wrangling the data on the possibility of getting something worthwhile from it. The way forward is not clear, so further effort is deferred.

According to University One, the perception among staff interviewed is that the success of Learning Analytics implementation is dependent on upper management sponsorship and the provision of scaffolded implementation strategies, that is to say ready-made templates that can be customised and deployed with relatively little effort. Success will be contingent on senior executive facilitating efficient ways of using the Learning Analytics technology. Success will therefore depend on who is in those senior positions.

Discussion

These are the "early days" of learning analytics (LA) in higher education. Optimized ways of using Learning Analytics are evolving in cycles of continuous improvement and doing so uniquely at each university. We note that each is evolving their own style in the absence an external, consensus-driven standard for how Learning Analytics can or should be used. This is a "double-edged sword" in the sense that the absence of standards is making it difficult to know how best to proceed, but it also opens up the field to a great many possibilities for those with energy and imagination.

The current situation favours proprietary platforms like Tableau[©] if said producers offer an off-the-shelf, customizable service that delivers real value in a user friendly way. We are likely to see more competition in this field, given the size of the higher education sector and the imperative to attract students.

The experience in University One shows that participants see potential in Learning Analytics but are not at all sure about how best to derive it. Given busy work schedules, the necessary trial and error effort over an extended period is likely to be a bridge too far for many course convenors. University Two is using their proprietary platform in constructive ways that demonstrate the effectiveness of their approach. University Three is pursuing a course-by-course strategy that is delivering value but in the less predictable manner than that seen with University Two.

One thing is clear, digital interventions such as learning analytics can do much to improve and inform teaching and learning practices. But it needs to be systematized for easy implementation, and must deliver tangible benefits over time.

This research expands the scope of use for Delone and McLean model as a descriptive tool. More in-depth qualitative research is needed to investigate this topic to gain a more high-resolution view of the situation. We

note that in a review of 180 academic papers utilizing the Delone and McLean model, only four were qualitative studies (Petter, Delone and McLean, 2008). While Learning Analytics is concerned with the quantitative management of the teaching and learning process, quantitative studies are useful for understanding those “soft” factors like culture that are difficult to quantify but are nonetheless important.

Conclusion

While Learning Analytics is in its infancy, it nonetheless has an important role in the on-going improvement of the teaching and learning field. As a priority, Learning Analytics must seek to provide the benefits of improved user satisfaction. Petter, Delone and McLean (2008) suggest that higher levels of user satisfaction are indicated by more frequent and intensive system use. We conclude that increased net benefits, as seen in the Delone and McLean model, can be derived from using Learning Analytics leading to higher levels of user satisfaction.

Analysis of the data suggests that when conducting research in the area Learning Analytics one should clearly define what is meant by that term in view of there being different interpretations. Universities could implement Learning Analytics systems that are either *student facing* or *academic facing*. The stakeholders and implications for Learning Analytics design will be different with each scenario. It should also be noted that the term Learning Analytics is an umbrella that covers many different systems. Learning Analytics is also frequently used to identify at-risk students as well as being used in a “recommender” capacity. These are among the first uses universities attempt when implementing Learning Analytics systems. This research has also shown that the benefits outweigh the challenges in terms of implementing Learning Analytics to improve teaching and learning.

While the Delone and McLean model was considered in the collection of data for this research study, more specific research will be performed to examine specific elements from the model using a qualitative lens. The researchers plan to revisit the case study universities and explore in greater depth the concepts around functionality, use and intention as related to learning analytics. As the Learning Analytics implementations were in their preliminary stages of implementations, it will be instructive to revisit and examine issues such as functionality once the systems have been in place for some time.

References

- Alhadad, S. J. (2018). Visualizing Data to Support Judgement, Inference, and Decision Making in Learning Analytics: Insights from Cognitive Psychology and Visualization Science, *Journal of Learning Analytics*, Volume 5(2), 60–85.
- Ally, M. (Ed.) (2009). *Mobile learning: Transforming the delivery of education and training*. Athabasca University Press (e-book). Retrieved from <http://www.aupress.ca/index.php/books/120155>
- Antwi, S., and Hamza, K. (2015). Qualitative and Quantitative Research Paradigms in Business Research: A Philosophical Reflection. European Journal of Business and Management, 7(3), 217-225.
- Beynon-Davis, P. (2013). *Business Information Systems*, Palgrave.
- Boyd, D., and Crawford, K., (2012). Critical Questions for big data, *Information, Communication and Society*, 15:5, 662-679. Retrieved from http://www.tandfonline.com/doi/abs/10.1080/1369118X.2012.678878#U_lr_UhAzu0
- Braun, V., and Clarke, V. (2008). Using thematic analysis in Psychology, *Qualitative Research in Psychology*, 3:2, 77-101.
- Campbell, J., and Oblinger, D. (2007). Academic analytics: White paper. Educause. Retrieved from <http://net.educause.edu/ir/library/pdf/pub6101.pdf>
- Coates, H. (2007). A model of online and general campus-based student engagement. *Assessment & Evaluation in Higher Education*, 32(2), 121-141.
- Colvin, C., Rogers, T., Wade, A., Dawson, S., Gasevic, D., Buckingham Shum, S., Nelson, K., Alexander, S., Lockyer, L., Kennedy, G., Corrin, L., and Fisher, J. (2016). Student retention and learning analytics: a snapshot of Australian practices and a framework for advancement. Canberra, ACT: Australian Government Office for Learning and Teaching. Retrieved from <https://research.monash.edu/en/publications/student-retention-and-learning-analytics-a-snapshot-of-australian>
- Coombs C.R., Doherty N.F. and Loan-Clarke, J. (2001). The importance of user ownership and positive user attitudes in the successful adoption of community information systems. *Journal of End User Computing* 13(4), 5–16.
- DeLone, W. H.; McLean, E. R. (1992). *Information systems success: the quest for the dependent variable*. *Information Systems Research*. 3 (1): 60–95.
- DeLone, W.H., and McLean, E.R. (2003). *The DeLone and McLean model of information system success: a ten-year update*, *Journal of Management Information Systems* 19(4), pp. 9–30.

- Donoghue, G. M., Horvath, J. C. and Lodge, J. M. (2019). Learning analytics and teaching a conceptual framework for translation and application, Routledge, Oxon.
- Gerbic, P. and Maher, M. (2008). Collaborative self-study supporting new technology: The Mahara e-portfolio project. In *Hello! Where are you in the landscape of educational technology? Proceedings ASCILITE Melbourne 2008*. Retrieved from <http://www.ascilite.org.au/conferences/melbourne08/procs/gerbic.pdf>
- Gunn, C. and Peddie, R. (2008). A design-based research approach for eportfolio initiatives. In *Hello! Where are you in the landscape of educational technology? Proceedings ascilite Melbourne 2008*. Retrieved from <http://www.ascilite.org.au/conferences/melbourne08/procs/gunn.pdf>
- Herrington, A. (2008). Adult educators' authentic use of smartphones to create digital teaching resources. In *Hello! Where are you in the landscape of educational technology? Proceedings ascilite Melbourne 2008*. Retrieved from <http://www.ascilite.org.au/conferences/melbourne08/procs/herrington-a.pdf>
- Järvinen, P. (2001). *On research methods*, Juvenes-Print, Tampere, Finland.
- Kearsley, G. (2004). *Explorations in learning and instruction: The theory into practice database*. Retrieved from <http://tip.psychology.org/>
- Klein, H., and Myers, M., (1999). A Set of Principles for Conducting and Evaluating Interpretive Field Studies in Information Systems. *MIS Quarterly*, 23 (1), 67-94.
- Koronios, A., Gao, J., and Selle, S. (2014). Big Data Project Success – A Meta Analysis. Pacific Asia Conference on Information Systems. Retrieved from <http://aisel.aisnet.org/pacis2014/376>
- LAK (2011). 1st International Conference on Learning Analytics and Knowledge, Banff, Alberta, February 27–March 1, 2011, as cited in George Siemens and Phil Long, "Penetrating the Fog: Analytics in Learning and Education," *EDUCAUSE Review*, vol. 46, no. 5 (September/October 2011).
- Lefoe, G., Philip, R., O'Reilly, M. and Parrish, D. (2009). Sharing quality resources for teaching and learning: A peer review model for the ALTC Exchange in Australia. *Australasian Journal of Educational Technology*, 25(1), 45-59. Retrieved from <http://www.ascilite.org.au/ajet/ajet25/lefoe.html>
- Leclercq, A. (2007). The perceptual evaluation of information systems using the construct of user satisfaction: case study of a large French group. *The DATABASE for Advances in Information Systems* 38(2), 27–60.
- Levy, P. (2006). 'Living' theory: A pedagogical framework for process support in networked learning. *ALT-J: Research in Learning Technology*, 14(3), 225-240. Retrieved from <http://repository.alt.ac.uk/138/>
- Levy, Y. and Ellis, T. J. (2006). A Systems Approach to Conduct an Effective Literature Review in Support of Information Systems Research. *Informing Science*, 9, 181-212.
- Lockyer, L., Heathcote, E., and Dawson, S. (2013). Informing Pedagogical Action: Aligning Learning Analytics With Learning Design. *American Behavioral Scientist* 57(10), 1439-1459.
- Long, P. D., and Siemens, G. (2011). Penetrating the fog: Analytics in learning and education, EDUCAUSE Review Online. Retrieved from <http://www.educause.edu/ero/article/penetrating-fog-analytics-learning-and-education>
- McAfee, A., and Brynjolfsson, E. (2012). Big Data: The Management Revolution, *Harvard Business Review*, 90 (10), 59 – 68. Retrieved from <https://hbr.org/2012/10/big-data-the-management-revolution/ar>
- Nguyen, T. D., Nguyen, T. M., and Cao, T. H., (2015). Information Systems Success: A literature review, Springer International Publishing Switzerland 2015, T.K. Dang et al. (Eds) FDSE, LNCS, (9446) 242-256
- Petter, S., Delone, W., and McLean, E. (2008). Measuring information systems success: models, dimensions, measures and interrelationships, *European Journal of Information Systems*, 17:3, 236-263.
- Rowley, J. (2002). Using case studies in research. Retrieved from http://www.psyking.net/HTMLobj-3843/using_case_study_in_research.pdf
- Scheepers, S. R., Scheepers, H. and Ngwenyama, O. K. (2004). Contextual influences on user satisfaction with mobile computing: findings from two healthcare organizations. *European Journal of Information Systems* 15(3), 261–268.
- Siemens, G. (2010). What are Learning Analytics? Retrieved from <http://www.elearnspace.org/blog/2010/08/25/what-are-learning-analytics/>
- Siemens, G. (2013). Learning Analytics: the emergence of a discipline, *American Behavioral Scientist*, 57 (10) 1380-1400, Sage Publications.
- Siemens, G. and Baker, R. S., (2012). Learning analytics and educational data mining: towards communication and collaboration, *Proceedings of the 2nd international conference on learning analytics and knowledge*, 252-254.
- Siemens, G., Dawson, S. and Lynch, G. (2014). Improving the quality and productivity of the higher education sector: policy and strategy for systems-level deployment of learning analytics, Retrieved from <https://www.voced.edu.au/content/ngv%3A64739>
- Slade, S., and Prinsloo, P. (2013). Learning Analytics: Ethical Issues and Dilemmas, *American Behavioral Scientist*, 57 (10), 1510 – 1529.
- Strang, K., (2016). Do the Critical Success Factors from Learning Analytics Predict Student Outcomes? *Journal of Educational Technology Systems*, 44 (3).

- Universities Australia (2013). A smarter Australia: An agenda for Australian higher education 2013 – 2016. Canberra, ACT: Universities Australia. Retrieved from https://www.universitiesaustralia.edu.au/ArticleDocuments/209/An%20Agenda%20for%20Australian%20Higher%20Education2103_2016.pdf.aspx
- Van Barneveld, A., Arnold, K. E., and Campbell, J. P. (2012). *Analytics in higher education: Establishing a common language*. EDUCAUSE learning initiative, 1(1), 1-11.
- Walsham, G. (1995). The Emergence of Interpretivism in IS Research. *Information Systems Research* 6(4), 376–394.
- West, D., Huijser, H., Heath, D., Lizzio, A., Toohey, D., Miles, C., Searle, B., Bronnimann, J. (2015). Learning Analytics: Assisting Universities with Student Retention - Literature Review. Retrieved from <https://researchrepository.murdoch.edu.au/id/eprint/35134/>
- Yin, R. K. (1984). *Case Study Research: Design and Methods*, Beverly Hills, Sage Publications, California.
- Yin, R. K. (2011). *Qualitative Research from Start to Finish*, The Guilford press, New York.

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