

How can DIT academic staff use Blackboard data and reporting to make better informed decisions around student learning?

Draft submission of Research Introduction and Literature Review

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Introduction

The almost ubiquitous adoption of LMS (Learning Management Systems) by HEI (Higher Education Institutions) provide extensive digital footprints left behind by students in their online engagement with LMS. It provides vast amounts of data which can be analysed for academia thereby gaining greater understanding of student cohorts. LA (Learning Analytics) offers HEI a means to predict student success, identify at-risk students and improve tailoring of course instruction to meet the needs of the students (NGLC, 2013, p. 1; Barneveld, Arnold, & Campbell, 2012, p. 6), thus deepening our understanding of the scholarship of teaching and learning. SoLAR, (Society for Learning Analytics and Research) defines 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” (SOLAR, 2013, p. 1).

In response to increasing demands for student success and institutional accountability, HEI witnessed a surge of interest in data mining and learning analytic technology to identify at-risk students and increase student retention. (Campbell & Oblinger, 2007, p.3; DeBlois, Campbell, & Oblinger, 2007, p.41). LA offers a lens into student learning and has been identified as one of the “fastest growing areas of research into technology-enhanced learning” (DEHub, 2012, p. 8). It has been cited in four consecutive Horizon Reports from 2011 to 2014 as an emerging technology impacting on teaching, learning and research (Johnson, Smith, Willis, Levine & Haywood, 2011; Cummins, Johnson & Adams, 2012; Johnson, Adams Becker, Cummins, Estrada, Freeman & Ludgate 2013) with the latest report expected to witness its impact in the next 12 months (NMC, 2014).

LA is largely an emerging field in educational research but analysis of LMS student engagement can provide a starting point for LA initiative. The focus of the research is to explore LA in the context of Dublin Institute of Technology’s (DIT) LMS namely Blackboard Learn 9.1. LMS e.g. Blackboard Learn, Moodle and Desire2Learn track and store vast quantities of data on students and their engagement with course content. Information gleaned from LMS can provide valuable insights to teaching and learning. The proposal aims to examine the data and reporting features available through Blackboard Learn to determine

if it assists lecturers and students in making better informed decisions regarding the student learning.

Aims and Objectives

The aims and objectives of research study are summarised below

- Identify relationships between student activity, LMS variables and how this may impacts on final grade
- Host workshop demonstrating data analysis features of Blackboard and measure effectiveness of same.
- Evaluate data analysis features of Blackboard e.g. retention center, and module reports.
- Capture lecturers' perceptions of learning analytics and their evaluation of the data analysis features of Blackboard.

Literature Review

Essa describes the tools we build for LA as being “akin to telescopes or microscopes that will hopefully allow us to see deeper, wider into student learning” thus optimising the student experience (Chalex, Essa, & Norris, 2012). Drysdale asserts analysing student data is becoming more and more commonplace within HEI, specifically when it influences students engagement and retention (2013, p1). Commercial companies have used data mining techniques for years, treating their data as an asset and using it for competitive advantage (Barneveld, Arnold, & Campbell, 2012). LMS is considered at the “frontline of LA” due to its ability to capture and store vast amounts of data in real time (Swan, 2012 p.5-6).

The literature provides several examples of HEI who have undertaken LA initiatives. One of the flagship projects for LA, Purdue University’s Course Signals (Arnold, 2010, p. 2), integrated student data from a range of instructional systems including student information system (SIS), library system and LMS to implement an early warning system based on a traffic light system. Using this data, the system generates a risk level with supporting information for each student, represented by a green (no risk), yellow (caution), or red indicator (high level risk indicator). Commenting on this system, Willis, Campbell, & Pistilli claim that by “receiving regular, actionable feedback on their academic performance students were able to alter their behaviours in a way that led improved course performance” (2013, p. 2). Paul Smith’s College in the US (Taylor & McAleese, 2012), Rio Salado College (Smith, Lange, & Huston, 2012 p. 51-60) and the University of Michigan (Lonn, Krumm, Waddington, & Teasley, 2012) are some of the many examples of Universities that developed early warning system.

Blackboards Learn 9.1 has an inbuilt early warning system entitled Retention Center. The system categorises at risk students based on four factors namely (a) missed deadlines, (b) grades, (c) course activity and (d) course access (Blackboard, 2013). Notably, when questioned which factors are highly predictive of student success across different courses, Course Signals creator John Campbell named those referred to above (Feldstein, 2013 p 1). Using Retention Center, academic staff are able to identify and communicate with at-risk students, providing additional support were required.

To narrow the scope of this study the criteria for literature review focused on previous LMS data mining studies.

Researchers at Brigham Young University analysed in excess of 36 million click counts and found announcements, content, grades, quiz, discussion board and communication constituted about 90% of all activity in Blackboard (Graham & Griffiths, 2009, p. 290). The paper highlights concerns regarding the utilisation, or lack thereof, of LMS. Carvalho, Areal, & Silva citing (Badge, Cann & Scott;Hall 2006) state that despite LMS adoption in HEI, concern is expressed as to whether LMS is being used as effective learning tools or merely as data repositories. Dyckhoff, Zielke, Bültmann, Chatti, & Schroeder note similar findings stating LMS tends to be used primarily for uploading documentation (2012, p. 58). To capture a more detailed view of LMS engagement, staff who frequently use the system were sought to participate in this study rather than those who simply view it as a data repository. Research studies focusing on LMS usage can potentially inform instructional design of online courses and diffusion of technology. Latour, Heck, Brouwer, & Moes used data analysis to determine if LA can support academia to effectively redesign a course based on collected and processed data, the results of which provided possibilities for course redesign (2013, p1). LA can identify which teaching techniques are more effective than others (Campbell & Oblinger, 2007) and assists lecturers in removing any barriers in existing course content or delivery. Dawson et al. (2008, p. 224) make an interesting point regarding the web 2.0 technologies embedded within LMS. They contend that data gleaned from LMS can be used to “guide and inform the diffusion of technology and integration into learning and teaching activities.” Such findings enlighten lecturers of the technology tools most effective in their teaching practice.

A report published by the Australian Learning and Teaching Council (ALTC) identified positive correlation between student participation in discussion forums and final results (Dawson & Mc William, 2008, p. 4). Similar studies identify active site engagement, time on task as an effective predictor of course outcomes in LMS (Smith, Lange, & Huston, 2012, p. 60; Beer, Jones, & Clark, 2010, p.81; Dawson, Tan, & McWilliam, 2008; Fritz, 2013, p. 1; Whitmer, Fernandes & Allen, 2012, p.6). In one of these studies Dawson, Tan, & McWilliam found that student activity within LMS peaked just prior to exams (2008, p.226). Their findings identified other peak periods could prove valuable as it could potentially assist academia communicating with the majority of their student cohort or possibly intervene in real time to assist underperforming students. Despite the claims that LMS activity, time on task and a student’s final grade are positively correlated, Abdous, He & Yen studies suggests that not all LMS variables directly relate to final grade. They found that online student video streaming participation cannot reliably be used to predict final grades (2012, p 85). Agudo-

Peregrinaa, Iglesias-Pradasa, Conde-Gonzálezb & Hernández-García analysed LMS activity in an online model and a hybrid model. The finding here is a relation between some form of interaction and academic performance in an online model whereas the relation was non-significant in a hybrid adopted model (2014, p 542-550). This raises consideration for research as the majority of modules (n=5) are LMS supported face to face courses and one module (n=1) is strictly online.

Studies have demonstrated other LMS variables, for example online quizzes are an effective resource to increase student performance. Studies seeking to evaluate the efficacy of online quizzes demonstrates students who partake in online quizzes fare significantly better than those that do not (Johnson & Kiviniemi, 2009; Orr & Foster, 2013; Dietz-Uhler & Hurn, 2013 citing Dietz-Uhler & Hurn 2012, p21). Of interest will be what hidden patterns, relationships, interdependencies or trends, if any, emerge during the quantitative phase of this research.

Macfadyen & Dawson (2010, pp. 589-590) cite the importance of the social nature of learning referring to educators increasing recognition of the benefits associated with learning and teaching that embrace socio-constructivist principles. Social Networks Adapting Pedagogical Practice (SNAPP) is a social network analysis tool providing visual aids depicting interactions amongst staff and students (Bakharia, Heathcote, & Dawson, 2009). It captures engagement/participation in online learning communities as it constructs relations based on forum interactions thereby identifying where socio-constructivist goals are achieved. The research aims to incorporate the SNAPP tool into Blackboard Learn to analyse discussion forum activity within chosen modules. It envisages the tool will provide real time visual representation of participation among students in discussion forums on Blackboard. Social network analysis has been “demonstrated to assist educators in identifying learner isolation and community formation”. (Dawson & Bakharia, 2011, p. 3)

The findings referred to above highlight a limitation of confining data analysis to LMS. It does not capture face to face dialogue between lecturer and student nor does it capture student engagement with social media tools that reside outside LMS. This has been raised by Siemens & Long (2011) who assert that analytic models do not capture library use, access to learning support or face to face discussions with academia. While addressing the problems that arise from capturing the dialogue between lecturer and student in a classroom is difficult,

criteria for selection of course modules in this study will be based on academia that utilise the web 2.0 features within Blackboard.

Dawson, Heathcote & Poole (2010, p. 7-9) raise a salient point regarding the integration, or lack thereof, of current disparate institutional systems for data mining purposes. The authors assert HEI should not limit data analysis to LMS but rather seek to integrate data from other sources such as (SIS) student information systems or records of previous academic history, therefore providing academia with more detailed and greater understanding of their student cohort. Similarly Johnson et al state to move LA forward it must include more than just LMS data and aspire to incorporate data from other sources (2012 , p. 22) Despite this assertion, the 2011 Horizon Report highlight difficulties encountered in integrating ICT systems for data mining purposes as it requires “capturing data from different disparate sources, often in different formats” (Johnson et al ,2011 p.29) . Blackboard provides a learning analytics solution entitled Blackboard Analytics (Blackboard, 2013) that could potentially address this problem as it integrates SIS and LMS. However this platform is not currently in use in D.I.T and is therefore not being reviewed as part of the research. Data integration from multiple ICT systems is not a consideration for this project in its current state but potentially identifies an area for further research

The literature highlights a noticeable lack of research investigating the inbuilt reporting and data analysis features of Blackboard. Given the technical difficulties and limitations encountered in extracting or combining data from LMS with third party tools (Dawson & Mc William, 2008, p. 6) I find it remarkable that more research has not been conducted into the analysis of inbuilt reporting in recent years. There are a few exceptions to this assertion , Dringus claims information generated from Blackboard reporting is limited, stating ”none of the views are synthesised and in single views none show important pieces of student progress” (2012, p.92). The aforesaid report published by ALTC is critical of Blackboard’s analysis features, referring to the reportage of data as “complex and confusing” (Dawson & Mc William, 2008, p. 6). This report, citing (Mazza & Dimitrova, 2007) refers to the extraction and reporting of LMS data as being fragmented. Of importance are two key points with this report, (a) the study was conducted in 2007/2008 and (b) it refers to Blackboard v8.0. The Institute is currently using Blackboard Learn v9.1. It is reasonable to suggest these features would have advanced in the interim. Tella cites some important factors for measuring Blackboard success such as content, system and service quality etc (2011, p. 72).

Notably data analysis or reporting features of Blackboard do not feature in this study. I find this remarkable considering data mining and LA are relevant issues in education today

Another significant report uncovered during the literature review was the ECAR 2013 report. It revealed intriguing findings, in that in two successive years students reported LMS “most pervasive and valued of technology resources” (Dahlstrom, Walker, & Dziuban, 2013, p. 11). Of the HEI surveyed, 70% view LA as a major priority but only 10% collect system generated data needed for analytics (p. 35). In line with this, (Siemens & Long, 2011, p. 32-33) affirm that HEI have traditionally been inefficient in their use of data. This is further proof that LA is still in its infancy and it maybe upwards of two to three years before we see its impact in HEI (Johnson et al., 2013, p. 24)

Despite the promise of LA the literature highlights some concerns.

- Data privacy is a major concern for LA. At the first Learning and Analytics Knowledge (LAK) Conference in 2011, all attendees present agreed it raises “deep and complex privacy issues” (Brown, 2011, p. 3). Understandably students may perceive LA as an invasion of privacy as the monitoring and tracking of student online engagement raises the “specter of a digital big brother” (Norris, 2011, p. 2), while Diaz & Brown argue that LA is “tantamount to snooping” (2012, p. 8). Despite this (Arnold, 2010, p. 8) claims during the Course Signals Project five years of research no one student queried how their privacy was protected. I find this claim startling given the issue of data privacy prevalent in the literature. One particular facet of the ECAR 2013 report that resonates with me is the discussion regarding students’ lukewarm attitude to LA. Dahlstrom, Walker, & Dziuban addresses students’ concerns regarding data privacy, suggesting if we fail to approach LA in an open, transparent and thoughtful manner then students’ data privacy concerns will transcend any benefits derived from LA projects (2013, p. 32-36). Learners must be advised clearly as to what data is being used, the reason therefor, provide signed consent and be assured data is anonymised. This discussion facilitated the submission of documentation to Institutes Research Ethics Committee (REC). The study will ensure the privacy of participants is protected, data anonymised and the study strictly adheres to data privacy and ethical guidelines.

- Instructors may feel that LA “takes assessment out of the realm of human judgment and reduces it to numbers and statistics” (Norris, 2011, p. 2). The readings uncovered similar findings with Campbell & Oblinger’s (2007, p. 16) assertion that L.A projects may be perceived as “dehumanising the educational process”. Long & Siemens contend that despite the emergence of big data and analytics “experience and gut instinct have a stronger pull” when it comes to making educational decisions. This discussion raises the debate of data driven decision making versus data informed decision and is a potential challenge faced by HEI undertaking LA initiatives. This raises a potential topic to discuss during the quantitative phase of this study. My thoughts on LA closely align that of (Brown & Diaz, 2012, p. 3; Fritz, 2013, p. 9), who argue that the role of LA is to support decision making not supplant it. It should not be used by academics to abrogate their responsibilities in decision making as educators.

Methods

The study will adopt a sequential mixed method approach with a qualitative follow-up phase building on the initial quantitative phase (Creswell, 2009, p. 211). The criterion for selection of staff participants is based on frequent users of the Blackboard system. The snowball/referral sampling technique was utilised to identify staff. The snowball sampling technique is used when the researcher initially samples a small group of people relevant to the research question, and these individuals propose other participants who have experience or characteristics relevant to the study (Bryman, 2012). Six course modules will be analysed in this study, one module from Maths (n=8), one Chemistry module (tbc-online students), two Accounting and Finance modules (17) and two Food Science & Environmental Health modules (n=46).

The quantitative phase will involve the measurement and analysis of data gleaned from Blackboard reporting to identify key statistical information regarding student activity. This will include analysis of LMS usage and LMS variables including login times, grades, frequency of logins, time spent, user activity in forums and discussion boards, multiple choice quiz (MCQ) attempts, and results etc. Engagement with LMS course modules will be analysed against final grade for each of these modules in the first semester of the 2013/2014 academic year in order to identify what LMS variables, if any are indicative of student success. The table below outlines details of the quantitative phase.

- All 71 students accounts have been verified
- Data will be analysed for the first semester of the College year (16th September 2013 - 19th January 2014)
- As of January 27th 2014 five academic staff members and seventy one students have provided consent. No more staff members will be involved in this study.
- Given the difficulties encountered in trying to incorporate students in the online module. It has been agreed with the module instructor that the researcher will address these students face to face when they visit the D.I.T campus on February 6th.

- Student participation in this study will be open until the week ending February 9th
- Reporting and extraction of existing student data will commence week beginning Jan 27th. Any additional student who signs up to this study from Jan 27th – Feb 9th will have their data extracted from Blackboard.
- It is expected exam results for student participants will be available the week beginning Feb 10th/17th. Their results will be compared against their Blackboard data. All data will be strictly de-identified.
- Quantitative analysis is expected to be completed by end of February 2014.

Interviews to be conducted with staff participants will provide the qualitative data for this study. It is anticipated interviews will be carried out in late March 2014 or early April 2014 (no later than April 11th). They will follow a semi- structured approach with the objective of receiving feedback from participants on their evaluation of Blackboard data analysis features. During these interviews staff participants will have the opportunity to discuss the findings of the quantitative phase.

These interviews will be transcribed week commencing April 14th.

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