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Evaluating the Data Analytic Features of Blackboard Learn 9.1: An Academic Perspective

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Abstract

Learning Management Systems (LMS) track and store vast quantities of data on student engagement with course content. Research shows that Higher Education Institutes can harness the power of this data to build a better understanding of student learning. This study is an exploratory Learning Analytics initiative to evaluate the inbuilt analytic features available within Blackboards LMS solution namely Blackboard Learn 9.1 to determine if it informs academic staff on student engagement.

The two analytic features analysed in this study are Module Reports and Blackboard's inbuilt early warning system called the "Retention Center". Analysis of LMS variables extracted from these analytic features established a statistically significant weakly positive correlation between hit activity, login activity and student examination results. A statistically significant weakly positive correlation was also established between Multiple Choice Quiz (MQQ) score and examination results.

These findings suggest that activity within LMS, measured by logins, hit activity and results in MCQ's provide indicators of student academic performance. Lecturers involved in the study felt the analytic features provided them with a sense of student engagement with course modules and better understanding of their student cohorts.

Keywords: Learning Analytics, Blackboard, Retention Center, LMS reporting, Engagement

Introduction

The almost ubiquitous adoption of Learning Management Systems (LMS) by Higher Education Institutes (HEIs) provides 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. Learning Analytics (LA) offers HEIs a means to predict student success, identify at-risk students and improve tailoring of course instruction to meet the needs of the students (Barneveld, Arnold, & Campbell, 2012, p.6), thus deepening our understanding of the scholarship of teaching and learning. The Society for Learning Analytics and Research (SoLAR) 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, HEIs 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; Johnson, Adams & Cummins, 2012; Johnson, Adams Becker, Cummins, Estrada, Freeman & Ludgate, 2013) with the latest report expected to witness its impact in the next twelve months (Johnson , Adams, Estrada, & Freeman, 2014).

Learning Analytics is largely an emerging field in educational research but analysis of LMS student engagement can provide a starting point for a LA initiative. LMS e.g. Blackboard Learn, Moodle and Desire2Learn track and store vast quantities of data on students and their engagement with course content. The focus of this study is to explore LA in the context of Blackboard Learn 9.1. Information gleaned from LMS provides valuable insight to teaching and learning. The main objective of the study is to examine and evaluate the data and reporting features available through Blackboard Learn 9.1 to determine if it assists lecturers in making better informed decisions regarding student learning and their pedagogical approach.

Lecturers involved in this study attended a workshop to demonstrate the analytic features of Blackboard Learn 9.1. They were later interviewed to capture their evaluation of these analytic features together with perceptions of LA. The following sections outline the steps involved in the study. This paper provides an overview of the literature along with details of the research methodology employed. It outlines and discusses the findings and concludes with suggested recommendations for further study.

Literature Review

In a recording entitled *Learning Analytics: The LMS Perspective,* Essa describes the tools we build for Learning Analytics (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 Higher Education Institutes (HEIs), 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 et al., 2012). Learning Management Systems (LMS) are considered at the "frontline of LA" due to their ability to capture and store vast amounts of data in real time (Swan, 2012 p.5-6).

The literature provides several examples of HEIs who have undertaken LA initiatives. One of the flagship projects for LA, Purdue University's Course Signals integrated student data from a range of institutional sources including student information system (SIS), library 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 green – "no risk", yellow –"caution" or red indicator "high level risk indicator" (Arnold, 2010, p. 2). Commenting on the 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 to improved course performance" (2013, p. 2). Paul Smith's College in the US, Rio Salado College and the University of Michigan are some of the many examples of Universities that developed an early warning system. Blackboard Learn 9.1 has an inbuilt early warning system called the 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 queried 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 the Retention Center feature within Blackboard Learn 9.1, lecturers are able to identify and communicate with at-risk students, providing additional support when required.

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 namely Student Information Systems (SIS) or records of previous academic history, therefore providing lecturers with more detailed and greater understanding of their student cohort. Similarly Johnson et al state that to move LA forward it must include more than LMS data and aspire to incorporate data from other sources (2012, p. 22). However despite these claims in the 2012 Horizon Report, the 2011 Horizon Report highlights 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).

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 Long & Siemens (2011) who assert that analytic models do not capture library use, access to learning support or face to face discussions with lecturers.

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 study 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 tend to be used primarily for uploading documentation (2012, p. 58).

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 provide possibilities for course redesign (2013, p1). Learning Analytics can identify which teaching techniques are more effective than others (Campbell & Oblinger, 2007) and assists lecturers in removing barriers to learning and teaching in existing course content or delivery. Dawson, McWilliam & Tan (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 and 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 et al., 2008; Fritz, 2013, p. 1; Whitmer, Fernandes & Allen, 2012, p.6). In one of these studies Dawson et al. found student activity within LMS peaked just prior to exams (2008, p.226). Their findings identified other peak periods that could prove valuable as it could potentially assist lecturers 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 suggest not all LMS variables directly relate to final grade. They found online student video streaming participation cannot reliably be used to predict final grades (2012, p 85).

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 who do not (Johnson & Kiviniemi, 2009; Orr & Foster, 2013).

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 contructs relations based on forum interactions thereby identifying where socio-constructivist goals are achieved. Social network analysis has been "demonstrated to assist educators in identifying learner isolation and community formation" (Dawson & Bakharia, 2011, p. 3).

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) it is 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. 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.

The 2013 ECAR report revealed intriguing findings, in that in two successive years students reported LMS to be "most pervasive and valued of technology resources" (Dahlstrom, Walker, & Dziuban, 2013, p. 11). Of the HEIs surveyed, 70% view LA as a priority while just 10% collect system generated data required for analytics (p. 35). In line with this Long & Siemens (2011, p. 32-33) affirm HEIs 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 HEIs (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, that in five years of research not one student queried by what method their privacy was protected. This claim is startling given the issue of data privacy prevalent in the literature. An interesting facet of the ECAR 2013 report is the discussion regarding students' lukewarm attitude to LA. Dahlstrom et al. address student 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).

The "gut instinct v data" debate was a concern highlighted in the literature. Lecturers 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 Learning Analytics 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 therefore is a potential challenge faced by HEIs undertaking LA initiatives.

Methods

The study targeted four course modules at the commencement of the 2013/2014 academic year in Dublin Institute of Technology (DIT). Three lecturing staff and eighty four students representing the College of Sciences & Health and College of Business consented to partake in the study. The snowball/referral sampling technique was utilised to identify the lecturers involved in the study. This specific technique is used when the researcher initially samples a small group of participants relevant to the research question. The individuals propose others with experience or characteristics relevant to the study (Bryman, 2012).

The study interrogated data generated through student engagement with Blackboard Learn 9.1; the Learning Management System (LMS) in use within DIT. A sequential mixed method approach was employed with a qualitative follow-up phase building on the initial quantitative phase. Due to the sensitive nature of analysing LMS student data, approval was sought and granted by the DIT Research Ethics Committee before the study commenced. Lecturer and student participants were provided with an information sheet and consent form, all data was strictly anonymised and involvement in the study was voluntary; participants could withdraw at any time without comment or without affecting their relationship with the Institute.

The module reports feature within Blackboard Learn 9.1 was utilised to extract data from four LMS supported face to face course modules during the quantitative phase, two from the School of Accounting and Finance modules (n=44) and two from the School of Food Science & Environmental Health modules (n=40). Correlation analysis was carried out on LMS variables to determine what relationship, if any, exists between different variables. The LMS variables analysed as part of this study were provided via the module reports, namely overall time spent within a module, number of logins, Multiple Choice Quiz (MCQ) score, hit activity in content area and overall hit activity within the module. It is important to note that there is "no universally accepted criteria for applying the adjectives strong, moderate and weak to correlation coefficients" (State Examinations Commission, 2010, p. 33). For the purposes of this study the adjectives strong and weak were applied using the following criteria - strong positive correlation (r) - $0.6 \leq r \leq 1$, weak positive correlation (r) - $0 \leq r \leq 0.6$ (Project Maths Development Team, 2011, p. 6). Each correlation coefficient "r" value was measured for statistical significance using a Critical Value Table to determine if the result occurred by "chance" or if the "r" value represented statistically significance (Siegle, 2014).

The quantitative phase involved the measurement and analysis of data gleaned from Blackboard reporting to identify key statistical information regarding student activity. Reports were extracted, anonymised and analysed through Microsoft Excel and SPSS for existence of interdependencies, trends, patterns and relationships. Interrogation of LMS variables was conducted on login times, frequency of logins, student hits (click activity), grades, time spent on course and multiple choice quiz (MCQ) results. Two of the modules in this study used the discussion forum feature .The SNAPP tool was used to examine discussion forum activity for these modules, providing visual aids depicting student to student and student to staff interactions.

Lecturers extracted examination results for semester one from the Institute's Electronic Grade Book (EGB) and this information was provided to the researcher. Engagement with Blackboard modules were analysed against final grade for each student participant in the first semester of the 2013/2014 academic year to ascertain which LMS variables, if any, were indicative of student success.

Following analysis of Blackboard data, lecturers were provided with a summary of the findings for each of their student cohorts. A workshop was held with the lecturers demonstrating the inbuilt data analysis features of Blackboard. Lecturers were provided with a lesson plan outlining the requirements and learning objectives of the workshop. The learning activities carried out as part of the workshop aligned with these learning objectives. Initially the workshop was very structured and instructor led. Emphasis was placed on repetition and practice in order for the lecturers to become proficient with usage of the tools.

The second phase of the workshop was much more of a collaborative effort. The focus was very much on what "outcome" the participants wanted from the workshop. This phase facilitated an engaging and stimulating learning environment as we discussed and debated the merits of each report and attempted to tailor the workshop to meet the needs of the participant and his/her student cohort. The lecturers were provided with details of a website resource, http://webcoursesanalytics.wordpress.com. Lecturers were advised to use this website to as a means to "recap" the topics covered during the workshop. This website resource was designed and developed by the researcher as a resource tool to assist DIT in using the data analytic features of Blackboard Learn 9.1 .The website provides an introduction to Learning Analytics and the analysis features of Blackboard Learn 9.1. It consists of a series of videos created by Blackboard and the researcher, Blackboard user guides and a lesson plan to assist DIT staff in utilising the data analytic features of same.

Interviews conducted with the three lecturers provided the qualitative data for the study. A semi structured interview approach was employed in order to elicit feedback from lecturers on their evaluation of Blackboard data analysis features, the workshop and their perceptions of data analysis and learning analytics.

Findings & Discussion

The following section discusses the findings of the correlation analysis. It captures lecturers' feedback on the workshop, the data analytic features of Blackboard Learn 9.1 and discusses the main themes to emerge from the qualitative phase of the study.

Correlation Analysis

Second, third and fourth year student data was analysed in the study. A statistically significant weakly positive correlation between student hit activity in content area($r=.283$), overall student hit activity within the module ($r=.207$), logins($r=.296$) and their overall module result was established for all students analysed during the quantitative phase ($n=84$). These findings suggest that frequency of login and hit activity in Blackboard may serve as effective predictors of course performance. These results are broadly similar to Smith et al. (2012 , p.60) who identified a strong relationship between log in frequency and course outcome. Similarly Whitmer et al. found that student hit count and final grade were postively correlated within Chico States University's Learning Management System (LMS) (2012, p.6). Whilst Wolff, Zdrahal, Nikolov, & Pantucek (2013 , p.149) contend that "it is not possible to draw conclusions about students engagement based on click activity", it does however provide an indicator of student activity within LMS and these findings suggest the amount of hit activity within Blackboard Learn 9.1 may positively influence students' examination results.

Relationships between Learning Management System (LMS) variables and their overall grades strengthened positively based on academic progression. Fourth year students demonstrated the strongest positive correlation followed by third year and then second year students. A statistically significant strong positive correlation between students' logins (r=.635, n=27), student activity inside the content area(r=.672, n=27) and student activity inside the overall module (r=.678, n=27) was established for the fourth year students, whilst a statistically significant weakly positive correlation was determined between time spent on Blackboard and final grade for both the third (r=.542, n=17) and fourth year (r=.484, n= 27) students. No other statistically significant correlation was established for the LMS variables for the remaining student groups. These findings may be influenced by high performance exams at the end of a four year degree program whereby students are aiming to achieve a merit or distinction and not just pass the course (interviewee1, personal communication, April 16, 2014). These findings need further research before they can be substantiated as feedback from the interviews suggest a large number of lecturers use LMS solely as a data repository and its usages can vary from one student cohort to another. Despite this, it does indicate the fourth year students yield more benefit than their third, second and first year counterparts in this study, as the analysis demonstrates the frequency of logins and hit activity can be an effective predictor of examination result.

Two of the four modules involved in the study used the discussion board feature i.e. third (n=17) and fourth year students (n=27). The SNAPP tool was utilised to analyse discussion forum activity of those students (n=44) and identified a total of 286 posts, averaging 6.5 posts per student. Discussion forum activity analysed against final grade highlighted similar findings to Dawson & Mc William (2008), weakly positive correlation was established between engagement in discussion forums and final grade (r value = .242, n=44). The lecturer who taught the students asserted discussion forum usage was "not required as any part of assessment criteria…students preferred to use Facebook as a forum for discussion" (interviewee1, personal communication, April 11, 2014). This may explain why the link between those two variables does not present a stronger correlation value. The finding closely aligns with Long &Siemens (2011) argument that confining data analysis to LMS does not capture all student engagement, in this case with social media tools that reside outside LMS and in this instance Facebook.

Analysis of the relationship between Multiple Choice Quiz (MCQ) scores and exam performance determined MCQs can be an effective predictor of course performance. In figure 1, a statistically significant weakly positive correlation was established between MCQ score and final exam result (n=28, r= .347). The impact of MCQs on exam performance was further evidenced by results provided during the interview stage by one of the lecturers. Following the workshop, one of the lecturers involved in the study conducted his\her own analysis. The lecturer held three MCQ assessments during the course of the second semester in which all topics covered in these three MCQs would be reassessed in his/her students' final exam (n=168). A statistically significant weakly positive correlation was established with each of the three MCQ scores when compared to the final exam result indicating the result the students achieved in each of these assessments was an effective predictor of their final examination result. These findings closely align with Johnson & Kiviniemi (2009) and Orr & Foster (2013) who demonstrated that online quizzes are an effective resource for increasing student performance.

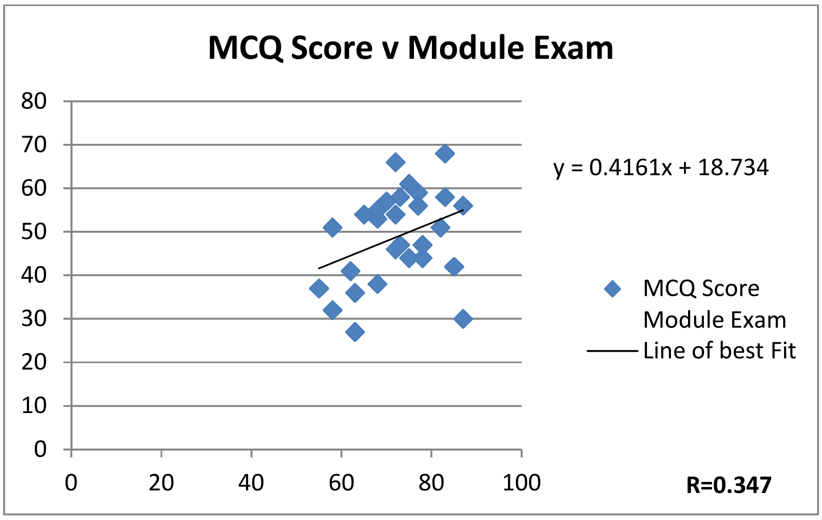
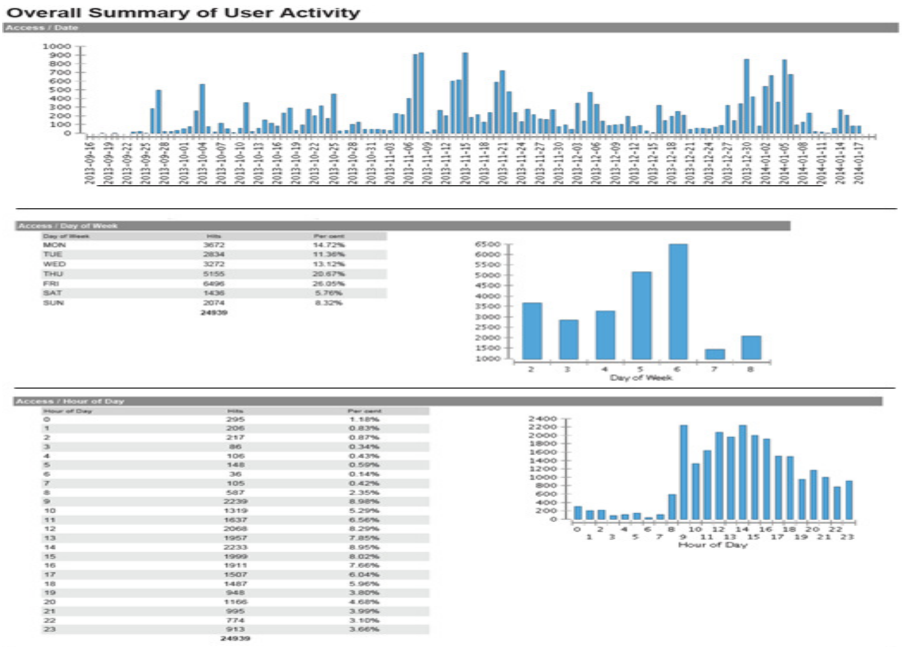


Figure 1: Performance of second year students (n=28) in MCQ assessment v Module exam

Blackboard Learn 9.1 Reporting Charts

Figure 2 displays charts produced by the "overall activity report" within Blackboard. This report illustrates user activity in all areas of the module by month, days of the week and hours of the day for one of the student groups involved in the study. All lecturers in the study agreed that the larger peaks in user activity within Blackboard coincided with assessment results or examinations for their respective student cohorts. The smaller peaks in user activity in the monthly chart were representative of "release of new lecture material and/or resources" (interviewee3, personal communication, May 14, 2014). Dawson et al (2008, p.226) identified similar findings in their study, claiming that larger peak periods of activity "correspond to assessment periods" supporting the notion that students are likely to be more engaged with Blackboard around assessment period. Dawson et al. raise an interesting point that could have implications for communicating with "at-risk" students, they contend that these activity charts highlight peak periods for staff intervention. For instance, if a lecturer knows when the majority of his\her student cohort is logged into LMS, it may represent an opportunity to communicate with potential "at-risk" students, possibly via email or an inbuilt chat room within Blackboard.This report could be beneficial to lecturers working with distant learning students in a strictly online environment in which availing of direct "face to face" time is often not possible. However these charts might identify periods to communicate with his/her student(s).



Day of Week	Hits	Per cent
MON	3672	14.72%
TUE	2834	11.36%
WED	3272	13.12%
THU	5155	20.67%
FRI	6496	26.05%
SAT	1436	5.76%
SUN	2074	8.32%
	24939	

Hour of Day	Hits	Per cent
0	295	1.18%
1	206	0.83%
2	217	0.87%
3	86	0.34%
4	106	0.43%
5	148	0.59%
6	36	0.14%
7	105	0.42%
8	587	2.35%
9	2239	8.98%
10	1319	5.29%
11	1637	6.56%
12	2068	8.29%
13	1957	7.85%
14	2233	8.95%
15	1999	8.02%
16	1911	7.66%
17	1507	6.04%
18	1487	5.96%
19	948	3.80%
20	1166	4.68%
21	995	3.99%
22	774	3.10%
23	913	3.66%
	24939	

Figure 2: Breakdown of user activity by month, week and hours of day

The chart represented by figure 3 illustrates students' engagement within the various features of Blackboard. During the interview stage it transpired that this chart was erroneous. One of the lecturers involved in the study used the wikis feature with his\her students but the chart failed to display any wiki usage. Email correspondence with Blackboard support confirmed that "this was a bug (LRN-67946) that was fixed in 9.1 SP 14. So, versions prior to SP 14 will not provide this information" (E-mail correspondence, April 17, 2014). Despite the omission of wikis usage, interviewees found figure 3 useful in guiding their teaching practice as it highlighted tools/areas for further usage or exploration. Interviewee1 frequently used the journal feature with his/her student cohort and viewed the chart by way of monitoring engagement within certain features of Blackboard stating "now that it is highlighted, I can look at journals and discussion forums and say look there is not enough activity in there" (personal communication, April 16, 2014). Another interviewee remarked "I would like to see the students use more features but I think the students are probably limited by me, rather than me being limited by the students…for next year I am determined to get discussion boards working" (interviewee2, personal communication, April 11, 2014). These remarks are particularly interesting in light of the findings of the literature review. In line with Dawson et al claim that data gleaned from LMS can be used to "guide and inform the diffusion of technology and integration into learning and teaching activities" (2008, p. 224). In line with Latour et al. (2013), usage charts i.e. figure 3 can potentially highlight areas for course redesign and inform lecturers regarding their pedagogical approach as to what LMS features may require further usage or exploration. For instance a lecturer might wish to see greater usage of the journal or discussion board feature by his/her students. The overall summary of user activity could facilitate a lecturer in re-designing their course layout in order to place greater emphasis on such features.

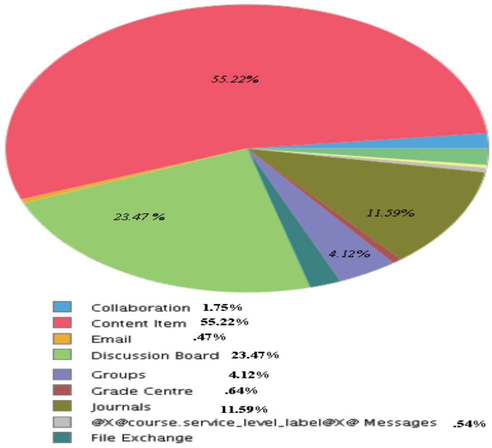


Figure 3: Overall summary of user activity displays breakdown of usage of features

The course activity overview report enables lecturers to view the length of time students spend in modules and where they spend it. Each blue bar displayed in figure 4 provides a link to a further report called "Student overview for a single course" which gives a further breakdown of where each student spent his/her time and the number of times they logged in. The orange line represents the average time spent by all students in the Blackboard module. When referring to the report, interviewee1 asserted that it is "very indicative of who is engaging and not engaging" (personal communication, April 16, 2014) while interviewee3 claimed "I can get the pulse of the student population in the class" (personal communication, May 14, 2014). This report could facilitate staff in identifying "at-risk" students as it provides them with a snapshot of the length of time students are logged into Blackboard and therefore identify students who are not logging in or who are falling well below the class average.

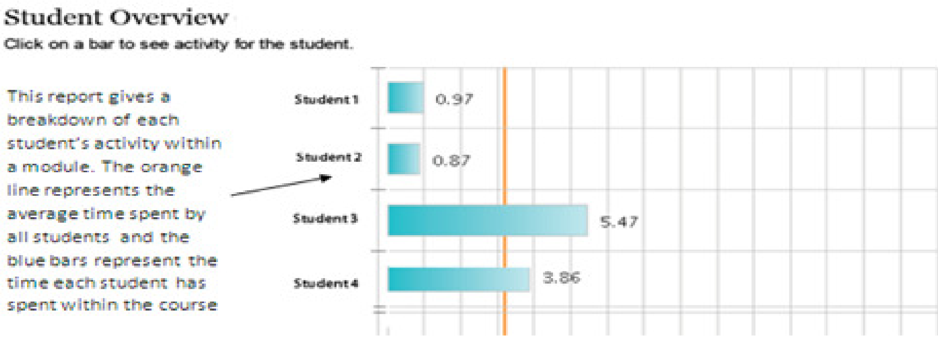


Figure 4: Output chart of the course activity overview report

Workshop/Resource

The workshop represented the first time that Blackboard Learn analytic tools were explored in any real detail by lecturers involved in the study. The knowledge acquired during the course of the workshop enabled lecturers to "make immediate use" (interviewee2, personal communication, April 11, 2014) of the analytic features to monitor student engagement with their respective Blackboard modules. Two of the interviewees managed to review the resource with interviewee1 stating "It will be of great assistance to all staff intending to use the analytical features" (personal communication, April 16, 2014). Interviewee3 highlighted the need for staff training and asserted the resource and further workshops should be accessible to other staff within the Institute, "I think this definitely shouldn't go on a shelf... it needs to be integrated into LTTC [Learning, Teaching & Technology Centre] training … possibly as part of a Blackboard module… so that staff can understand its potential" (personal communication, May 14, 2014).

Module Reports

Contrary to Dawson and Mc William's assertion that teaching staff do not use LMS reports, they opine as "too complex and confusing" (2008, p6), all lecturers involved in the study asserted that once the main features had been demonstrated they found the reports were relatively straightforward to use and they continued to use them since the workshop. The output from the reports e.g. those described in figures 2-4 facilitate lecturers in monitoring and driving student engagement in LMS. Interviewee1 remarked "I would see this technology as a way of driving continuous learning, especially when you set deadlines for journals, wikis and whatever. Now you can go and monitor that. Without this transparency it is impossible to drive student engagement" (personal communication, April 16, 2014).

Interviewee2 highlighted significant, yet compelling, criticisms of the reports in their existing format. Currently the reports extract information based on a student's engagement within a module. A feature is not provided to capture engagement across all modules for a student.

> If I could find a way whereby I could overlay your module on my module and see who is using all the modules or who is using none of them and come up with a total picture of student over the six modules they are doing in any one semester... we would have something quite powerful (personal communication, April 11, 2014).

The suggestion was endorsed by other lecturers in the study who felt it would enable staff to be aware of students engaging consistently across all modules or if usage peaks on some modules more than others. Further criticism by interviewee3 referred to the location of the reporting features within Blackboard, claiming they are not "clearly visible" (personal communication, May 14, 2014) when logging into Blackboard and if they were more prominent it may encourage more usage.

Retention Center

Prior to the workshop just one of the three lecturers involved in the study used the Retention Center. The lecturer in question had previously attended a workshop hosted by the LTTC which provided an overview of the Retention Center. The lack of usage of this feature was further evidenced in the quantitative study whereby Retention Center accounted for just 0.1% usage for all four modules involved in the study. The ability to create and customise existing rules was cited as an important aspect. It is important "we can adjust the scale of when to flag alerts in Retention Center…customisation of alerts depends on the module and assessment approach as some Blackboard modules might require more engagement than others" (interviewee3, personal communication, May 14, 2014). One of the interviewees claimed that:

> A lot of students can get away with leaving work towards the end of the semester… they might not seem to be engaging early on but then have a burst of activity. Retention Center will come into play when deadlines are given for work to be done that you have to capture. In the absence of them, it is probably not meaningful (interviewee1, personal communication, April 16, 2014).

This provides further evidence of the necessity to tweak or customise the default rules as the lecturer deems appropriate. Some lecturers utilise web 2.0 technologies like wikis and discussion forums and expect daily or weekly engagement while others simply use it for document repository. Therefore fortnightly engagement may suffice. It is important to adjust the rules to suit individual student(s) requirements, otherwise lecturers will receive too many/few alerts that may dissuade them from using the feature. All lecturers agreed that the inbuilt rules were "reasonably good" predictors of student success.

Other themes to emerge from the interview stage of the study are summarised below.

Data Privacy

Analysis of student data makes it difficult to escape the issue of data privacy and data protection. As previously referred to, the ECAR report cites students' lukewarm attitude towards Learning Analytics (LA) whereby analysis of student data may be construed as eavesdropping (Dahlstrom, Walker, & Dziuban, 2013). Interestingly the feedback on this was extensive. Interviewee2 felt "ethically bound" (personal communication, April 11, 2014) to advise students their data in Blackboard may be monitored whilst interviewee3 claimed it was their "job to analyse Blackboard data to see how their students are engaging" (personal communication, May 14, 2014). Interviewee1 expressed concern about securing sensitive data, "if employers were to get their hands on such data it could potentially damage a students employment prospects" as they may be able to determine if the student is a consistent performer or not (personal communication, April 16, 2014).

All lectuers were adamant that monitoring student data is done for the students indiviual and collective benefit. Openness and transparency are key factors in building student confidence in data mining exercises, as was evidenced by interviewee2 assertion:

> I am very conscious of data privacy issues…I would be very clear about what I am doing, I am collecting data to encourage students, to motivate students, to find problem students and to try and find out what the problems are (personal communication, April 11, 2014).

These findings demonstrate that monitoring of student data, when done for the right intentions to promote learning and help identify students who may be at risk and when put to good use trumps ethical issues.

Data privacy remains a thorny issue. These findings clearly demonstrate monitoring of students is carried out ultimately for their benefit. It highlights an area for further research as the data collected does not capture students' perceptions of data analytics and perhaps student consultations or questionnaires in a future iteration of this study may shed light on the issue.

Engaging with At-Risk Students

Following the workshop one of the interviewees used reporting data relating to a student missing lectures. In discussions with the student, interviewee2 was advised the student was following it all on Blackboard. However following the workshop, interviewee2 extracted LMS reports to discover that this was not entirely accurate and subsequently approached the student asking "does 25 minutes on Blackboard substitute for eight hours lecturing". The purpose of this intervention was not to be perceived as "big brother" but rather assist students who may be "at-risk" in terms of academic progression or dropout, "it is done for the purposes that you want the student to succeed" (personal communication, April 11, 2014).

All lecturers felt the data analytic features equipped them to deal with potential "at-risk" students but one of the interviewees alluded to the challenges of dealing with the personal side of this issue:

> The analytics is impersonal, it's cold, it's calculated...but the question is once you identify which students or student is having problems, or might have a problem, the kind of contact and pastoral side of ….nearly all staff would need a little bit more training on that how do you deal with a student who may have personal circumstances (interviewee3, personal communications, May 14, 2014)

In view of this finding, HEIs such as DIT may consider the necessity for more training to address the challenges in dealing with "at-risk" student(s).

Data Driven Decisions

Despite Long and Siemens (2011) assertion that "experience and gut instinct have a stronger pull" over data, two of the interviewees viewed it as a combination of both, suggesting that putting both of these together will yield the best results. The remaining participant leaned more towards data driven decisions claiming that with large class sizes it is difficult for a lecturer to know if all their students are engaging but “good data will highlight issues before they reflect themselves in dropout or poor performance” (interviewee1, personal communications, May 14 , 2014). The author opines this issue closely aligns that of Diaz & Brown (2012, p. 3) and Fritz (2013, p. 9), who argue that the role of Learning Analytics is to support decision making not supplant it. Therefore it should not be used by academics to abrogate their responsibilities in decision making as educators.

Dispersed Information Sources

All lecturers would like to see greater integration of data from different sources. They referred to the difficulties that arise in module and progression boards with borderline decisions regarding student progression or students achieving a distinction or merit, – “at the moment you have to go into various different systems such as Infoview and Banner to find information about a student” whereas if data was collated into one system it would facilitate this decision making process and allow a lecturer to “build a case for a student” (interviewee3, personal communications, May 14, 2014).

Another lecturer claimed that despite the benefits of the analytic tools, they “do not capture the single most important bit of data which is class attendance” (interviewee2, personal communications, April 11, 2014). Currently there is no requirement in DIT to record class attendance. However the lecturers involved in this study manually record attendance before each lecture via a sign in sheet. This poses a problem in that it uses valuable time in class to manually enter the attendance records into an excel file. All lecturers felt that if there was a means of capturing class attendance into Blackboard Learn 9.1 it would facilitate them in their roles as educators and build a richer student profile - “we are monitoring more than enough Blackboard features, what I would like to see added is class attendance” (interviewee2, personal communications, April 11, 2014). These findings closely align with Johnson et al (2011), i.e. integration of data from disparate Institutional sources is a challenge faced by HEI in attempting to build a richer profile of their student cohorts.

Recommendations

The author recommends further promotion and awareness of the analytics features should be disseminated to lecturing staff in DIT. The author, along with members of the Institute’s Learning Teaching and Technology Centre (LTTC), have sought to address this issue by hosting the resource created as part of this project on the LTTC website. A possible avenue to promote the tools may be to conduct a series of training workshops throughout the academic year and to host a workshop as part of the annual D.I.T eLearning Summer School. It is envisaged this would capture a wider audience and the ideal platform to raise awareness of the analytics features available within Blackboard Learn 9.1 thus providing lecturing staff with the requisite skills and knowledge to monitor and analyse their students’ LMS engagement and identify potential “at-risk” students.

For further research the author recommends development of the study to include data from other institutional sources such as Student Information Systems or, as the feedback from the interviews suggest, incorporating class attendance with the data to build up an in-depth student profile. Blackboard offer their own analytics solution namely Blackboard Analytics, perhaps a one year pilot phase could be sought to integrate this platform with the existing LMS used in DIT to build a richer profile of the Institute’s students.

Conclusion

In conclusion, the combination of hosting a workshop and adopting a blend of qualitative and quantitative techniques gave a comprehensive view of lecturers’ evaluations and perceptions of Blackboard Learn 9.1 reporting and data analytics. One of the unique aspects of the study is lecturers were afforded the opportunity to explore the tools after the workshop and in advance of the interviews which led to a more detailed evaluation of same. Learning Analytics (LA) is still in its infancy stage. It is an emerging tool which needs to evolve in terms of sophistication, popularity and effectiveness, particularly with Irish Higher Education Institutes. One of the main objectives was to evaluate the information produced by Blackboard Learn 9.1 analytic features to access the impact of student engagement with same. Extraction of LMS variables i.e. logins, content hits, overall module hits and MCQ assessments demonstrated statistically weakly positive correlation with exam performance, suggesting that these variables can serve as effective predictors of student academic performance. The study shows that the data and reporting features facilitate academic staff in learning more about the activity of their students in Blackboard. The analytic features available within Blackboard Learn provide indicators of engagement for students and provide academic staff with further knowledge and monitoring capabilities regarding their students' interactions, or lack thereof ,with the Blackboard Learn 9.1

One of the main concerns to emerge from the study is the lack of awareness of the existence of the analytic tools in Blackboard Learn 9.1. The author's contention is that without the workshop and creation of the website resource it would have been difficult to influence lecturers and convince them of the benefits of utilising these data analytic tools. Emerging technologies, i.e. Learning Analytics, require research and training to see beyond the "fog" and access its impact for teaching and learning before academics and indeed students advocate its use. The work carried out over the duration of this study highlights greater need not just for DIT staff training on the analytic features available within Blackboard Learn but also the personal aspect of dealing with "at-risk" students.

Siemens, Gasevic et al. cite the broad goals of LA to include the improvement of completion rates and providing decision makers with needed information regarding learners (2011). Whilst the scope of this paper is much narrower, it highlights benefits that can be derived from such studies and that with more training and access to resources, such as the one created for the project, analytics can play a prominent role in informing lecturers regarding their students' LMS engagement.

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