ascilite
ascilite 2012
FUTURE CHALLENGES | SUSTAINABLE FUTURES
25 - 28 November 2012 | Wellington | New Zealand

Early identification of students at risk of failing

John Milne
Massey University

Lynn M Jeffrey
Massey University

Gordon Suddaby
Massey University

Andrew Higgins
Andrew Higgins Ltd

This paper outlines how teachers can use the learning management system (LMS) to identify at risk students in the first week of a course. Data is from nine second year campus based business courses that use a blend of face-to-face and online learning strategies. Students that used the LMS in the first week of the course were more likely to pass. For the rest of the course the pattern of usage is then largely similar for students who pass and those that do not pass. This paper identifies how a LMS can identify at risk students in the first week of the course and provides some strategies to motivate these students.

Keywords: At risk students, learning management system, early intervention, student success

Introduction

Tools are available to track participation in a learning management system (LMS). Teachers can get reports in a LMS on who has or has not used the LMS or some aspect of it. For instance Moodle keeps a log of each screen that the students visit. Teachers can then filter results by student name, date, activity and action. More sophisticated tools are available that allow the teacher to visualise clusters of student usage data that allow the teacher to look at student performance or behaviour (Hall et al, 2009; Hangjin & Almeroth, 2010; Lee, Chen, Chrysostomou, & Liu, 2009). Many of these tools are complex and are not easy for the teacher to use (Romero, 2011).

A number of papers have explored the association of LMS usage and student success. Cocea and Weibelzahl (2009) used data mining techniques to examine student behaviour that predicted disengagement. They found that student behaviour of time spent reading pages and taking tests were associated with student engagement. Altinay and Paraskevas (2007) found that those who rarely post to discussion forums are at risk of failure. Baugher, Varanelli, and Weisbord (2003) found that consistency of LMS use was a better predictor of success than total hits. Buglear (2009) found that some students who drop out do not use the electronic system so that this may also be a good indicator of students who are at risk of not completing the course.

A pilot study suggested that there was an association between students' use of the LMS and final grades. Students who use the LMS in the first week of the semester were more likely to pass. This paper aimed to test this association with data from another eight courses. Patterns of usage over the semester were examined to identify differences between students who pass and those who fail. This data is discussed using the student engagement literature of Kahu (2011) and Jeffrey, Milne, Higgins and Suddaby (in press).

Methods

The LMS logged students' usage over the semester for nine campus-based courses involving 703 students. The courses offered students campus-based lectures and tutorials with a LMS that had resources, forums, assignment upload and feedback facilities, and in some courses, online quizzes. The number of times a student downloaded a LMS resource or activity was recorded and the results summed for each week over the semester. The usage patterns over the semester are presented for students grouped by their overall course marks. Four groups were tracked based on final marks. These were students who achieved an A or B pass, C pass, fail, or did not complete. The distribution of marks across the categories was not even. On average across nine courses the percentage of students in each category is: 50% obtained an A or B; 30% obtained a C; 11% failed; 9% did not complete. The class sizes ranged from 23 to 147 with a mean of 78.

The data from the first week of the course for the students who completed the course was analysed. There were 658 students who sat the final exam. Those who did not complete were removed from the analysis because the wide range of non-teaching related reasons for withdrawing were considered to cloud the issue. Students who complete the course show determination and perseverance that were considered likely to respond to teacher interventions. The students were grouped by those that: did not use the LMS; used it for 1 to 5 page views; used it for 6-20 page views or for over 20 page views. The percentage who passed the course were identified in each category and associations tested by a chi square.

Results

The usage for the first week of the semester was compared to the number of students who passed the course (Figure 1). Successful students were more likely to use the LMS in the first week for both the pilot (ChiSq=20.4, 3df, p<0.001) and main trial (ChiSq=19.5, 3df, p<0.001).

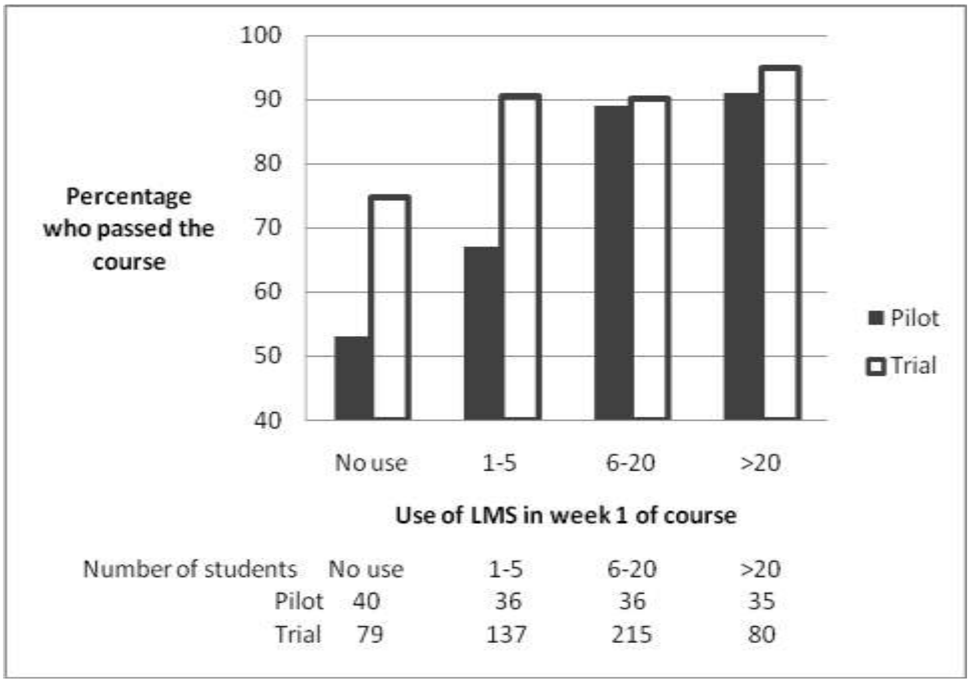

Figure 1: The number of students who passed the course grouped by use of the LMS in the first week of the Semester for the pilot and trial courses

The pattern of LMS use is provided in a sample of six courses (Figure 2). These graphs are characterised by peaks and troughs of activity with the peaks coinciding with the assessment. Week 7 and 8 were midterm breaks which did associate with a drop in activity in some courses but not all. Courses with assessment that is due immediately after the break had peaks of activity during the break. All but one course had a final exam that was associated with a final burst of activity. Course 5 (Figure 2) was internally assessed with a marked drop off of activity after the final assessment report.

The main difference in patterns of use between students who passed and those that failed relates to the very early stages of the course where students who fail are distinctively lower in online activity. It may be that after this stage, students are unable to catch up or that they have missed critical information or orientation to the course. This may mean that the first week, or the very early part of the course is critical to success and that later in the course measures such as total hits does not identify students who are struggling. Students who did not complete the course generally had lower use although some did use the LMS throughout the course.

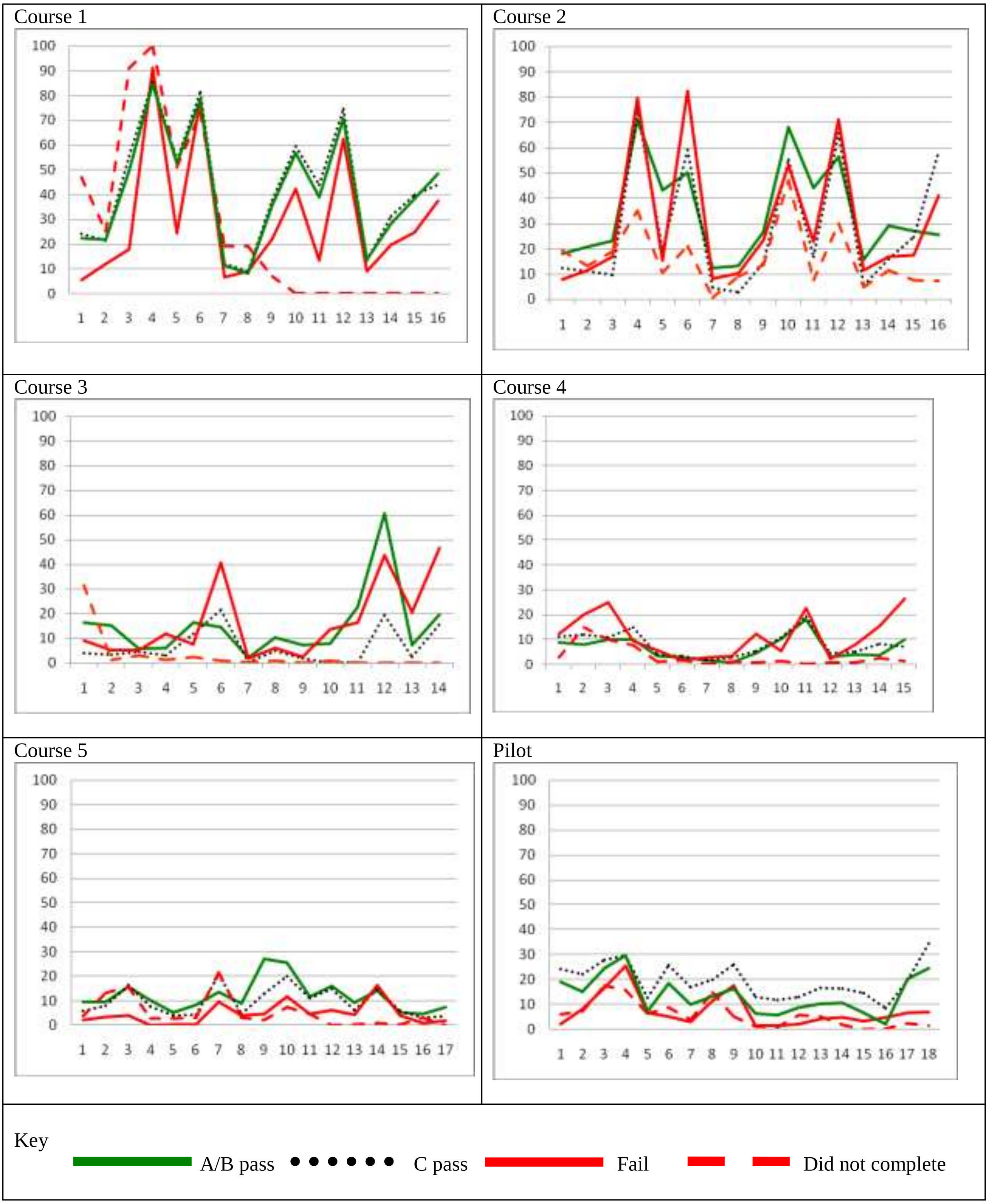

Figure 2: Graphs of students' use of LMS grouped by overall student success

Discussion

Successful students are purposeful and make good of use their learning time. This includes starting at the early stages of the course so they have enough time to learn. This paper has identified a simple approach that identifies students who are slow to start online activity. A significant percentage of this group (see Figure 1) will not pass and would benefit from some reminders to start work.

While there are a variety reasons for failing a course, such as student behaviour or subject choice (Trotter & Roberts, 2006), it is well established in the literature that successful students attend more face-to-face lectures than those who do not complete or fail (Fitzgibbon & Prior, 2003; Gracia & Jenkins 2002). The LMS offers lecturers an easy way to identify students who are may be at risk while there is still time to help the student. Ways to encourage at risk students to engage, or re-engage, include contacting them to remind them about getting started on the course, giving them information about time management and the support that is available including centralised learning support.

Engagement is the key to student success. There are a number of ways that lecturers can help students engage in their studies. Kahu (2011) provides a framework of engagement with three dimensions. These are Affect which is based on enthusiasm and belonging, Cognition based on deep learning and self regulation and Behaviour based on time and effort, interaction and participation. The identification of students who do have not logged in to the LMS in the first week involves using the behavioural dimensions of engagement and then reacting with strategies on the affect dimension to encourage students to become part of the group with the lecturer showing an interest in the student.

Lecturers need to understand how to improve retention and success. They can do this by understanding student engagement and use frameworks that Kahu (2011) and others such as Jeffrey, Milne, Higgins and Suddaby (in press) provide to alter student behaviour, cognition and affective elements of their learning.

References

Altinay, L., & Paraskevas, A. (2007). A computer-supported collaborative learning (CSCL) approach in teaching research methods. *International Journal of Hospitality Management*, 26(3), 623-644. doi: DOI: 10.1016/j.ijhm.2006.05.005

Baugher, D., Varanelli, A., & Weisbord, E. (2003) Student Hits in an Internet‐ Supported Course: How Can Instructors Use Them and What Do They Mean? *Decision Sciences Journal of Innovative Education*, 1, 159-179

Buglear, J. (2009). Logging in and dropping out: exploring student non-completion in higher education using electronic footprint analysis. *Journal of Further & Higher Education*, 33(4), 381-393. doi: 10.1080/03098770903272479

Cocea, M., & Weibelzahl, S. (2009). Log file analysis for disengagement detection in e-Learning environments. *User Modeling and User-Adapted Interaction*, 19(4), 341-385.

Fitzgibbon, K., & Prior, J. (2003). *Student expectations and university interventions: A timeline to aidundergraduate student retention.* Paper presented at the LTSN BEST Conference, Brighton.

Gracia, L., & Jenkins, E. (2002). An exploration of student failure on an undergraduate accounting programme of study. *Accounting Education*, 11(1), 93-107.

Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., & Witten, I. H. (2009). The WEKA Data Mining Software: An Update. *SIGKDD Explorations*, 11(1).

Hangjin, Z., & Almeroth, K. (2010). Moodog: Tracking Student Activity in Online Course Management Systems. [Article]. *Journal of Interactive Learning Research*, 21(3), 407-429.

Jeffrey, L.M, Milne, J.D., Higgins, A. and Suddaby, G.T. (in press). Strategies for engaging students. Helps and Hindrances in a blended learning environment. Ako Aotearoa. National Centre of Tertiary Teaching Excellence.

Kahu, E. R. (2011). Framing student engagement in higher education. *Studies in Higher Education*. doi:10.1080/03075079.2011.598505

Lee, M. W., Chen, S. Y., Chrysostomou, K., & Liu, X. (2009). Mining students' behavior in web-based learning programs. *Expert Systems with Applications*, 36(2, Part 2), 3459-3464.

Romero, C. (2011). *Handbook of educational data mining*. Boca Raton, FL: CRC Press.

Trotter, E., & Roberts, C. A. (2006). Enhancing the early student experience. Higher Education Research & Development, 25, 371–386. doi:10.1080/07294360600947368.

Author contact details:

John David Milne, J.D.Milne@massey.ac.nz

Please cite as: Milne, J.D., Jeffrey, L.M., Suddaby, G. & Higgins A. (2012). Early identification of students at risk of failing. In M. Brown, M. Hartnett & T. Stewart (Eds.), Future challenges, sustainable futures. Proceedings ascilite Wellington 2012. (pp.657-661).