Learning Analytics for Measuring Engagement and Academic Performance: A Case Study from an Irish University

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Abstract
This paper presents an analysis of various metrics of student engagement and academic performance, based on data extracted from a virtual learning environment (VLE) and other supporting technologies. The level of student activity on the VLE, as measured by hours and count of accesses to content areas, was found to be a strong indicator of engagement and impacted the level of performance. Participation in self-regulated optional learning activities was also found to be a strong indicator of engagement, which again impacted students' scores. As regards gender comparisons, males and females demonstrated different study approaches but there was no difference in performance. Senior (final year) students out-performed sophomore (second year) students, and students on programmes with higher entry bars fared better. Interestingly, students who adopted a steady approach with consistent levels of activity through the semester achieved higher scores than those who procrastinated. The paper concludes with some recommendations on where learning analytics technologies need to go to truly be useful for teachers and students in higher education.

Keywords: *Academic performance; Engagement; Student behaviour; Gender differences; Learning analytics; Virtual learning environments; Structural equational modelling.*

1. Introduction

This paper presents an analysis of the engagement and performance of students taking a course in "Database Systems for Business" at an Irish university. Prior research has highlighted the importance of engagement as a factor impacting retention and academic achievement (Hussain *et al.,* 2018). Levels of interaction, self-regulation (e.g. working on optional exercises), prior knowledge of the subject area, gender, and secondary school grades are also amongst the many factors that can impact performance in higher education (Pardo *et al.*, 2016; Koç, 2017; Pizarro *et al.*, 2017; Hellas *et al.*, 2018). An exploratory data-driven research approach as opposed to a theory-driven approach (Maass *et al.*, 2018) was followed. Student profile data and analytics from the Blackboard virtual learning environment (VLE) and other sources were combined and analysed to build up a picture of various indicators of engagement and to explore their impact on academic performance, as indicated by scores on the course assignment and end-of-semester test.

2. Teaching and Assessment Approach

The course was pursued by 59 students across four separate undergraduate programmes, running from September to December 2020. The class was 32% female and 68% male, all Irish nationals with the exception of two visiting international students. Because of emergency public health guidelines in force during the COVID-19 pandemic, the course moved out of the normal classroom environment and was taught fully on-line by means of a regular live two-hour session delivered on Microsoft Teams each week for the duration of one semester. Presentation slides, supplementary notes and other lecture materials were made available in advance on Blackboard and remained available on-line for the full duration of the course. The weekly lecture sessions were also recorded and shared on Blackboard.

The teaching style was interactive; as the lecturer worked through examples of problems, students were invited to ask and answer questions via the Microsoft Teams chat dialogue or by clicking the 'Raise Hand' button and speaking. Building on the material covered in lectures, students were provided with a set of practical exercises and formative assessment quizzes designed to prepare them for the end-of-semester test. Students could attempt the quizzes as often as they wished and received a feedback score each time upon completion.

The course was assessed by means of an assignment (30%, teams of two or three) and a final test (70%, individual). The assignment was based on the *Jay's Collectibles* teaching case (Cappel & Gillman, 2011) and required students to work together on a problem-based learning exercise to design a database schema. The lecturer made himself available for on-line consultation meetings with student groups seeking guidance on the assignment; most groups availed of this opportunity at least once. The end-of-semester test consisted of fifty multiple choice quiz (MCQ) questions, each with four possible options of which one and only one was correct. The first half of the test examined knowledge of database design concepts. The second half was based on knowledge of the Structured Query Language (SQL) and used the same familiar database schema as was employed throughout the course in the lectures and practical exercises.

This teaching and assessment approach incentivised students to attend lectures, engage deeply with the assignment, attempt the practical exercises and quizzes, and consult the other learning materials made available on Blackboard, which included a link to an electronic version of the recommended textbook. The fact that learning materials were made available on Blackboard had no impact on class attendance levels, which were in line with historical averages.

3. Learning Analytics

As summarised in Table 1, various metrics were extracted from the Blackboard VLE platform, Microsoft Teams and Microsoft Forms surveys and quizzes. The process of extracting and consolidating data into a clean, usable format was rather cumbersome and therefore these metrics were not available in real-time, only retrospectively after the course was completed.

Table 1. Learning analytics measures.

Measure	Description
anon_id	Anonymous identifier (all PII removed)
completed_year	Did student complete this academic year?
assignment_mark	Mark awarded for assignment
exam_mark	Mark awarded for end-of-semester test
programme_code	Degree programme code
final_year	Is this student in final year of degree?
overall_mark	Overall Mark (Assignment + Examination)
gender	Gender (Male or Female)
prev_knowledge_subject_area	Did student have any prior knowledge of the area?
how_many_others_do_u_know	How many other students in the class did this student know at beginning of semester?
bb_hours	Total hours of Blackboard access for this course
bb_access_lecture_materials_percentile	Extent of access to Lecture Materials on Blackboard
bb_access_recordings_percentile	Extent of access to Recordings on Blackboard
bb_access_practical_exercises_percentile	Extent of access to Practical Exercises on Blackboard
bb_access_textbook_percentile	Extent of access to Textbook on Blackboard
bb_activity_percentile_q1 / q2 / q3 / q4	Relative activity in Blackboard in each of the four quarters of the twelve week semester
teams_chat_interactions	Count of interactions on Microsoft Teams Chat
formative_quiz_attempts	Combined number of attempts at formative quizzes

4. Findings and Discussion

Exploratory non-parametric tests were executed in SPSS to seek out patterns of correlation and differences in the data.

A student's overall mark was found to be positively correlated with several influencing factors, including the number of hours that the student was active on Blackboard (N=57, $r_s = .474$, $p < .001$), the number of times that the 'Lecture Materials' section on Blackboard was accessed (N=57, $r_s = .493$, $p < .001$), and the number of times that a student attempted the formative quizzes (N=57, $r_s = .620$, $p < .001$).

Interestingly, the number of times that the 'Recordings' section on Blackboard was accessed did not impact performance. This can be explained by an observed range of types of study behaviours: some students who attended lectures also watched the video replays (those students mostly fared very well), but there were some who skipped lectures and just watched the videos (those students tended to perform relatively poorly).

The number of interactions on Microsoft Teams (i.e. questions and other posts in Chat) had a strong positive correlation on students' marks on the assignment (N=58, $r_s = .656$, $p < .001$) and also, but not to the same extent, on overall mark (N=57, $r_s = .542$, $p < .001$). This can be explained by the fact that many of the questions raised on Chat related more to the material assessed by the assignment than that assessed by the end-of-semester test. The students who asked those questions or otherwise contributed on Teams were highly engaged and therefore, in keeping with the findings of previous studies (Pardo *et al*., 2016, Hussain *et al.*, 2018), it was expected that they would perform better than less engaged students. Of course, some outstanding students did not interact at all on Teams, which can go down to personality differences such as introversion.

Similarly, the number of times that students accessed the 'Practical Exercises' section on Blackboard was found to have a strong positive correlation with their end-of-semester test mark (N=55, $r_s = .518$, $p < .001$), as did the number of times they accessed the textbook link (N=55, $r_s = .437$, $p < .001$). These are both examples of self-regulated learning behaviour.

An interesting finding was the correlation between activity at various points in the semester and performance on the end-of-semester test. The level of Blackboard activity for each student throughout the semester was broken into four quarters of three weeks each. Activity in the first quarter was found to be positively correlated with the test score (N=55, $r_s = .407$, $p < .01$) but the strength of this correlation fell in the second quarter (N=55, $r_s = .360$, $p < .01$) and again in the third quarter (N=55, $r_s = .342$, $p < .05$). In the fourth quarter, it was insignificant. What this suggests is that students who were consistently active throughout the semester fared better, whereas in the final quarter there was a mixture of last-minute "crammers" and "steady-does-it" students, with very different results achieved.

Two students who commenced the course did not complete and two others chose to defer. The latter pair was due to COVID-19 health-related issues and both subsequently passed. The former pair indicated at the beginning of the semester that they knew nobody else in the class (most students knew at least one other person), and their level of Blackboard activity in the first quarter was negligible. As it turned out, both students failed to complete not just this course but also several others. Given the early warning signs, these drop outs were predictable. Unfortunately, they were also unpreventable because of the underlying causes. Students who were in assignment teams with students that subsequently dropped out were discommoded to an extent, and this was taken into consideration by granting appropriate time and grading concessions on those submissions.

When looking at the content areas that males and females accessed, it was found that females accessed the on-line lecture materials ($N=59$, $U = 212$, $p < .01$), textbook ($N=59$, $U = 231$, $p < .05$) and formative quizzes ($N = 59$, $U = 224.5$, $p < .05$) significantly more often than male students, and that females spent a substantially greater amount of time engaging with materials on Blackboard ($N=59$, $U = 226$, $p < .05$). However, despite these gender differences in study approach, no difference was found as regards academic performance, as measured by assignment and end-of-semester test scores.

This study found that senior (final year) students had significantly higher performance than sophomore (second year) students on the end-of-semester test with mean GPA scores of 3.9 and 3.3 respectively ($N= 55$, $U = 553$, $p < .01$).

Surprisingly, students with no prior knowledge of the subject material actually fared better overall than those who had some previous exposure to the area ($N= 53$, $U = 235.5$, $p < .05$). This may be because of higher motivation of the newcomers to the subject area (who were mostly final year students) and possibly some degree of complacency amongst those with prior experience.

The programmes that students were enrolled in also gave rise to significant differences in scores. This can be explained by the varying academic entry criteria for the programmes. Not surprisingly, the students on programmes with higher entry standards (i.e. secondary school grades) fared, on average, better than those on programmes with lower entry bars.

To further explore the relationship between engagement and academic performance, a Structural Equation Model (SEM) was constructed using the Ωnyx environment (Onyx, 2022). The results of the SEM revealed that our data support the hypothesis that level of engagement impacts academic performance: χ^2 (6) = 60.002, CFI = 0.999, TLI = 0.995, RMSEA =.03. The resulting paths are shown in Figure 1. In earlier versions of the model, other variables were included but they were removed because of weak loadings and unacceptable impact on the model fit. As can be seen, the number of hours of Blackboard activity and the number of attempts at formative quizzes both loaded strongly onto the

'Engagement' latent variable, with statistically significant positive correlations of 0.72 and 0.87 respectively. The assignment mark and end-of-semester test mark both correlate positively with 'Performance', although the loading of the assignment mark was lower than expected. This may perhaps be because the assignment mark, unlike the other variables in this model, was not unique to each individual student (i.e. it was done as part of a team). Engagement had a strong positive correlation (0.76) with performance.

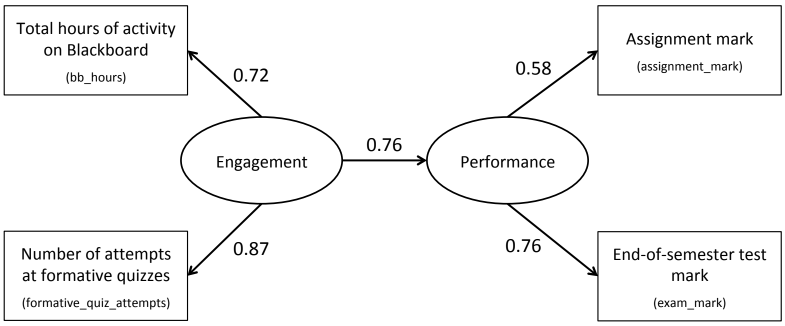

Figure 1. Structural equation model derived from learning analytics data.

5. Conclusion

The potential of learning analytics to provide teachers with valuable information pertaining to measures of academic engagement and performance is widely recognised (Koç, 2017; Kosasi *et al.*, 2020). Importantly, they also have the potential to provide students with personalised benchmarks of their own metrics so that they can stay on target to achieve their goals. For example, the findings of this study showed that levels of activity at early stages of the semester can impact overall performance, and that students who went 'the extra mile' on self-regulated activities fared better. A small number of students who were disappointed with their overall scores contacted the lecturer to enquire why they didn't do as well as they felt they would. In all such cases, an examination of the metrics discussed in this paper provided simple explanations. Had the students been easily able to see where they actually were, as compared to where they ought to have been or believed they were, they may have succeeded in achieving their ambitions.

The actual extent to which learning analytics are being purposefully used in universities across the world is unknown, but it is almost certainly the case that the majority of students and teachers are not using analytics to anywhere near their potential. Why is this the case? The Technology Acceptance Model (Venkatesh & Davis, 2000) tells us that perceived ease of use and perceived usefulness – which is affected by output quality, demonstrability of results, job relevance, and other factors – impacts actual usage behaviour. During the COVID-19 pandemic, educators hurriedly rushed to adopt on-line meeting and collaboration technologies (e.g. Zoom, Teams, Slack) that, to be fair, were mostly not intended for the purpose of teaching and learning. However, as we move into the "new normal" of post-pandemic on-line and hybrid delivery, the ease with which useful and timely learning analytics can be generated must be a factor in the choice of educational technologies.

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