

Data thresholds in learning analytics: Identifying priority students for proactive outreach

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Abstract

The University of Southern Queensland (UniSQ) has developed a Student Success Advising strategy that uses learning analytics to identify students who could benefit from support via proactive outreach. This paper describes the analysis and development of course Learning Management System (LMS) thresholds that measure the impact of student LMS activity on success. The establishment of these thresholds accurately identifies students at risk of failure and facilitates proactive outreach. These findings support targeted, data-informed interventions to improve student engagement, retention, and success.

Learning analytics can successfully identify students who could benefit from additional support and have demonstrably impacted student retention and success when contextualised to Australian institutions (West, et al., 2015). A user-centred clustering design with predictive analytics was found to be especially effective in cases that required complex advising and the exploration of multiple support scenarios (Gutierrez, et al., 2018). Dashboards that extend beyond descriptive data (e.g., grades) to report on real time usage of Learning Management Systems (LMSs) are more likely to support actionable and immediate intervention (Gutierrez, et al., 2018). For example, use of data pipelines demonstrated that the combination of low LMS activity and non-submission of an early assessment item accurately identified disengaged students (Linden, van der Ploeg, & Roman, 2023). Nevertheless, limited empirical evidence of the effectiveness and impact of university wide interventions based on learning analytics is the biggest challenge in the data generation, tracking, analysis, and action cycle of learning analytics (Wong and Li, 2020). This informed the development of the Student Advising Database project, which was based on the established value of student advising practices and the need to underpin this with evidence-based data and robust processes and systems.

The Initiative

The Student Advising Database project aims to use multiple historical and real time data inputs and outreach methods across a range of intervention types to understand the outcomes and effectiveness of university wide Student Success Advising (Ethics ETH2024-0562 (HREC) Low Risk). Data points include study characteristics (degree, basis for admission, load), LMS engagement levels, and academic performance (grades). Analysis was undertaken on one full year (2023) of historical LMS activity by 21,315 students across 1800 unique courses. This analysis determined a clear LMS engagement threshold where the level of activity in a course correlated with student grades to constitute an optimal point for proactive outreach.

Outcomes and insights

First, the analysis examined whether there was a correlation between level of LMS activity in a course and course grades, determining a clear correlation between students' activity and successful course outcomes. The more active a student in the LMS (i.e., the higher the activity of 'click' count), the more likely a student was successful in the course in terms of course grade.

Next, LMS interaction patterns were examined to determine which activities corresponded with a higher grade. Weighting of these activities, based on historical data, led to the development of a coefficient matrix for measuring impact of LMS features/activities on course success. The matrix reduced noise in the model by identifying critical variables to be used in the intervention calculation. Also important to the intervention calculation was the identification of a course LMS activity threshold (Threshold 1). This is an equation for determining the average click count, which starts to register once the average clicks for a course exceeds 600. Finally, the historical data was analysed to determine the threshold where a student's level of activity in a course led to an unsuccessful outcome. A clear threshold was identified (Threshold 2): when a student's LMS activity fell within the bottom 0 to 30th percentile range of the historical average activity for the individual course, the student's likelihood of failing grew to be over 80%.

These findings provide empirical evidence that a student who is disengaged from their studies as indicated by low LMS activity is more likely to fail their course. Determining the threshold for low LMS access and automation that accurately identifies when disengaged students are falling below the mean activity in their course has facilitated just in time, personalised, targeted and data informed supportive outreach. In 2023, 8282 students with no LMS access were identified. The turnaround time for identification was two weeks so only 40% of students could be contacted before census. Implementation of the thresholds in 2024 resulted in the accurate identification of 4776 students with no or low LMS activity. Turnaround time for identification was three days, which led to 88% of students receiving timely proactive outreach before census. It is anticipated that this will positively affect student engagement and progression.

Questions for audience discussion

1. LMS activity indicates student engagement in a course, what strategies have you used to re-engage students with no or low LMS access?
2. This initiative uses data points that include study characteristics, engagement levels, and academic performance. What student behaviour data points are you using that have had success in re-engaging students?

References

- Gutiérrez, F., Seipp, K., Ochoa, X., Chiliza, K., De Laet, T., & Verbert, K. (2020). LADA: A learning analytics dashboard for academic advising. *Computers in Human Behavior*, 107, 1-13. <https://doi.org/10.1016/j.chb.2018.12.004>
- Linden, K., van der Ploeg, N. & Roman, N. (2023). Explainable learning analytics to identify disengaged students early in semester: an intervention supporting widening participation. *Journal of Higher Education Policy and Management*, 45(6), 626-640. <https://doi.org/10.1080/1360080X.2023.2212418>
- West, D., Heath, D., Huijser, H., Lizzio, A., Toohey, D., Miles, C., Searle, B., Bronnimann, J., Lynch, G., Allan, G. & Edlund, G. (2015). *Learning Analytics: Assisting Universities with Student Retention, Case studies-Project outcome of Final Report*. Australian Government's Office for Learning and Teaching. https://ltr.edu.au/resources/SP13-3268_Casestudybook_2015.pdf
- Wong, B. T. M., & Li, K. C. (2020). A review of learning analytics intervention in higher education (2011–2018). *Journal of Computers in Education*, 7(1), 7-28. <https://doi.org/10.1007/s40692-019-00143-7>