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Back to the Future

Opportunities to improve learning analytics for student support when using online assessment tools

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Knowing when a student is being productive in an online learning environment is challenging to discern from online trace data. Custom built assessment tools, integrated into a learning management system (LMS), offer a way to obtain finer-grained data not commonly available in existing systems. An exploratory observational study of 1,822 assessment submissions in an online course of 500 students was conducted. All assessments were submitted utilising a new online assessment tool that offered embedded resources, feedback and tracked when words were typed or pasted into the tool. Students were hesitant to consistently use the online editor, moderately used the embedded resources and heavily utilised the feedback. There was moderate evidence that whether or not a student viewed the previous assessments feedback was a better indicator of future assessment success than LMS activity.

Keywords: learning analytics, online learning, feedback.

Introduction

Tertiary education has undergone significant change in the way institutions are expected to support their students. Historically, the onus was clearly on students to seek out support. However, expectations have shifted further and further towards a shared responsibility. Some have called this intrusive advising (Rodgers et al, 2014). With online learning environments becoming more common as technology improves, proactive support based on students' online activity is common practice (Linden & Webster, 2019). Within this context, knowing if a student is working on their upcoming assessment or not is clearly important, however, mapping online trace data to genuine student activity in an online learning platform is challenging (Beer et al., 2010; Wilson et al., 2017; Dringus, 2012). An acceptable level of digital surveillance within a Learning Management System (LMS) forms part of the social contract between student and educational institution, along with a shared understanding of the intended use of data (Arnold & Sclater, 2017; Corrin. et al., 2019).

As assessment and feedback remains central to student success in higher education it makes sense to have closer scrutiny of student activity around assessment tasks. This is even more critical in online subjects to help teachers support students (Kift, 2009; Kift & Moody, 2009), but the capacity of the educator to understand what a student is doing in their online course is inextricably linked to the technology surrounding how the student engages with content and assessment. Early warnings from missed early assessment items can help scaffold interventions to improve student success (Linden & Webster, 2019) but is it possible, with more fine-grained assessment activity data (such as live data on how many words have been written for the assessment) to identify students in need of support before the assessment is due?

Active time spent on a LMS is notoriously difficult to measure from log data (Beer et al., 2010), however online assessment platforms provide an opportunity to access data on learner assessment behaviour that has not previously been available. Logging of words typed into an assessment task, activity data directly tied to assigned work, has the potential of providing a cleaner live view of student workload and more accurate post hoc analysis. The overall aim of this exploratory study was to see if the online student activity, revealed in a newly implemented online assessment tool, could improve the capacity of an educator to support students prior to submission of an assessment. This is broken into two research questions:

RQ1: How did students engage with the assessment tool?

RQ2: Does the finer-grained assessment activity data offer new affordances for the support of students?

Methods

An online assessment tool, Cadmus (https://cadmus.io/), was piloted in a large, online, first year subject. Students were provided with phone and email support in using this new tool. Cadmus is designed as a cloud based document editor, embedded within the LMS, that provides real-time academic skills and integrity advice to students. From a learning analytics perspective the exciting prospect was the potential utility of having timestamped records of words typed and pasted into an assessment. A total of 559 students from a range of undergraduate courses across our large regional Australian university were enrolled in the subject, and 500 went on to submit at least one assessment item and were included in the analysis. These 500 students submitted a total of 1,822 assessments in the subject and completed their work over 20,059 separate sessions in Cadmus. Assessment was via 4 written tasks that students have previously found difficult. The first assessment item was a reflective piece due prior to the census date valued at 10%. The remaining 3 assessment items were a critique (20%), essay (40%) and the final assessment required structured writing valued at 30%. All four of the assessments in the subject utilised the online assessment tool. Ethics approval for this observational study was received from The Charles Sturt Human Ethics Committee (HREC Protocol No H21170).

For RQ1 student behaviour was visible in four metrics within the tool; words typed into the online editor, words pasted into the online editor, views of the embedded resources, and accesses to the feedback. Words typed or pasted into the online editor were also timestamped by the login session.

Regarding RQ2 the baseline used was LMS activity data, measured in clicks per day. Different data were available from the LMS (such as page views, time on site) but a single measure was used to avoid issues arising from collinearity. The additional data made easily accessible by the tool includes logs of when the student was working on the assessment, how content was added to the assessment (typed or pasted), accesses to the embedded resources (if present) to support the assessment, and accesses to the feedback provided after the assessment was marked. We explore how these new data might possibly describe student success in an assessment, measured by the (standardised) score the student received.

A linear regression model was created to compare the influence of four key variables on the standardised score outcome. The four predictors were chosen to simulate what the academic would know 1 week prior to the submission of an assessment as the aim is to find out what can be used to help support students. They are:

- **LMS activity**. This is measured as total clicks between 14 and 7 days prior to the due date, normalised according to the whole class in that time window. This is designed to simulate the teacher checking a student's relative activity in the past week, one week before the assessment is due.
- **Starting early**. *Yes* if the student began work on their assessment 7 or more days earlier than the due date, *No* otherwise.
- **Accessing resources**. *Yes* if the student accessed any of the designated resources for the assessment, *No* otherwise.
- **Viewing feedback**. *Yes* if the student viewed the feedback for the *previous* assessment, *No* otherwise.

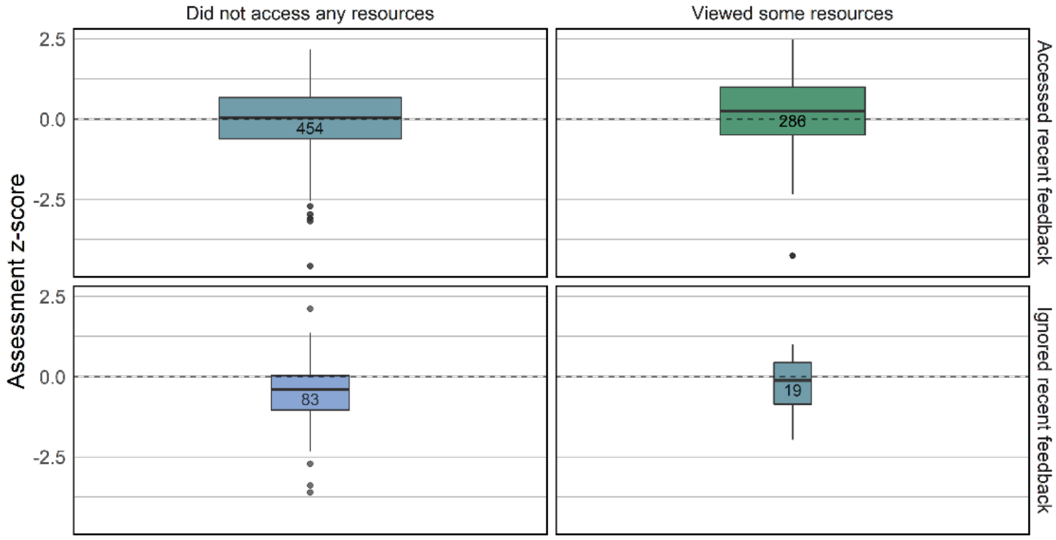
A Bayesian approach was adopted for direct interpretability of uncertainty and weakly informative (*Normal(0, 1)*) priors were used. Continuous variables (LMS activity) were standardised by dividing by twice the standard deviation to allow easier effect comparison with binary variables (Gelman, 2007), as the aim was for the model parameters to be interpretable as comparable effects on the assessment score. Models were built in R using the brms (Bürkner, 2017) and bayesplot (Gabry & Mahr, 2021) packages and all code is available here.

Results

Use of the Assessment Tool

Students favoured working offline and pasting their work into the tool when ready, particularly for the longer, later assessments. Overall students appeared to use the online tool 'in tool' around 35% of the time, with 277 (55%) of the students utilising it 'in tool' at some point during the course (see Figure 1).

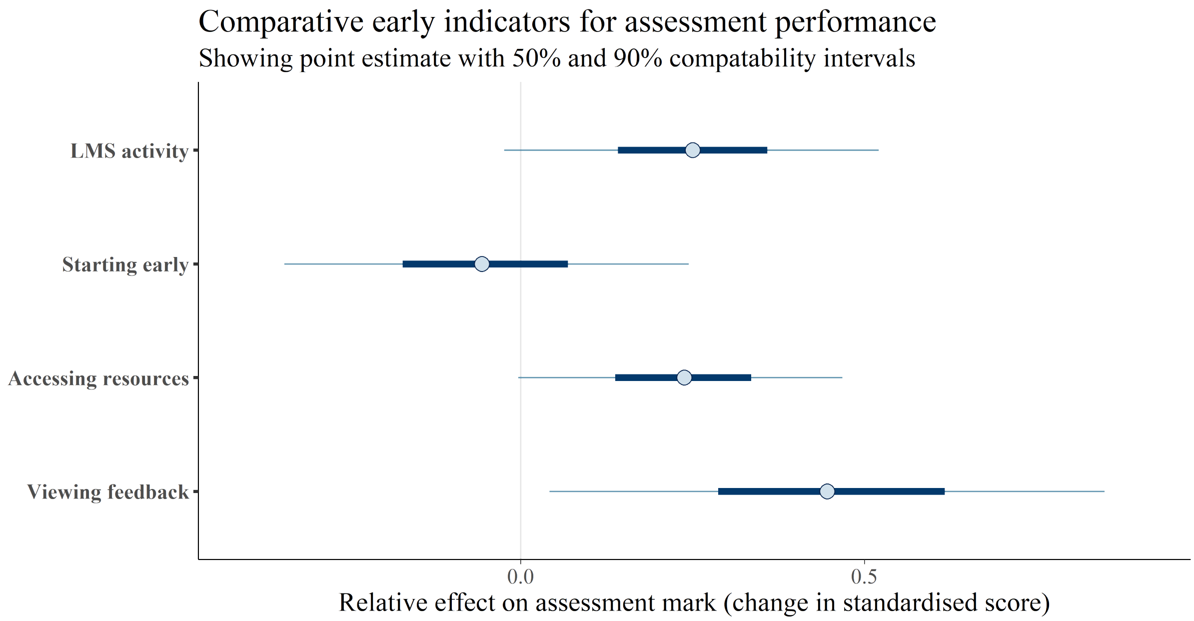
Figure 1. Contingency table of resource and feedback use, with assessment mark distributions. Each result here is for an individual assessment from those that had resources available



Where available (the *Critique* and *Structured Writing* assessments) the embedded resources and feedback were used by most students; 52% utilised both at some point in the subject, 55% viewed a resource and 92% viewed some feedback (with 78% viewing all their feedback).

Data Affordances

Figure 2. Model coefficient estimates. Positive values indicate a positive influence on the assessment score, knowing the values of the other variables



Viewing feedback of prior assessments shows a statistically significant positive effect in predicting future assessment results (the 90% compatibility interval was above zero). *LMS activity* and *Accessing Resources* possibly have a positive effect (50% compatibility interval above zero) but this remains uncertain. *Starting early* looks to have no predictive power in anticipating assessment score as the estimate is centred around zero (see Figure 2).

Discussion

In response to RQ1 it seems that students were reluctant to consistently use the online editor in the assessment tool, however most used the embedded resources and the feedback was utilised heavily. In terms of impact on assessment scores accessing the feedback of the previous assessment had a stronger influence than accessing the learning resources (see Figure 1 and also the modelling results), so it was both the strongest association with academic success and seemingly the most valued by students (Poulos & Mahony, 2008).

The importance of viewing feedback as a way to improve a students' learning outcomes is more than an intellectual curiosity for the teacher (van der Meer et al., 2018). When trying to predict future success *Viewing feedback*, high *LMS activity* and *Accessing resources* all have a positive effect, however the strongest was *Viewing feedback*. Indeed, the model offered moderate evidence that *Viewing feedback* may be a stronger indicator for future performance than *LMS activity*. This highlights the importance of a student reflecting on their work in order to improve. A logical extension of this study is to see if this behaviour can be altered to improve student performance. A student facing dashboard could easily be built to display key student behaviours that perform well and prompt students if they are slow to access feedback. This implementation does not require a specific assessment tool; any LMS that can track access to resources and feedback could be leveraged to do the same task.

Our project has been working on proactively identifying disengaged students who have not submitted an assessment item and offering targeted support (Linden et al., 2020). It was hoped that the pre assessment analytics could be used to identify students before the due date. We were surprised that the data was inconclusive regarding the impact of starting the assessment early. If you had hoped to find evidence here to support the detrimental effect of last minute cramming we are afraid your search continues.

Limitations

This was an exploratory study and results should be taken in that context; it involved a single subject, the students using the tool as expected self-selected and learning design choices (such as the use of resources) are purely observational. There is also possible confounding between the variables of the model, as is often the case in the complex world of learning (Davis & Sumara, 2006), and interaction effects were not considered for this initial study. For instance, you could posit that the (currently unseen) positive effect of *starting early* on an assessment is mediated through the *LMS activity* which would then be masked in the regression model used here; Lübke et al (2020) has explanatory examples that highlight this. Teasing out the genuine direct effects of the predictor variables requires more sophistication than what is presented here. Furthermore, this was the first time that students had used such a tool, so those that self-select into 'in-tool' usage of the online editor could be a qualitatively different subgroup to those more hesitant with early adoption of new technologies.

Conclusion

As noted in the limitations further work is required to build a model that can measure the direct effects of the available data on assessment outcome. Expanding this initial exploration to more subjects is a natural next step to see which patterns seen in the subject of study are robust to the change of context. Unfortunately, just over half of the students did not use the tool as intended, preferring to work offline and paste their work into the tool. It will be interesting to see if a higher percentage of 'in tool' compared to 'offline' workers is found elsewhere, or if students change their behaviour as they utilise the tool in future subjects. This might go some of the way to explaining why there was seemingly low take up of 'in tool' use, but further investigation would be needed to examine if this hesitancy is due to general hesitancy for using a new tool or if some of the reluctance stems from concerns around the fine granularity of the data collected.

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