GENERATING WEEKLY ENGAGEMENT PROFILES USING LMS-DATA TO PREDICT AT-RISK UNIVERSITY STUDENTS

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SUBTHEME: Empowering educators

BACKGROUND:

The introduction of Learning Management Systems (LMS) in tertiary institutions to accommodate the shift to online learning, has resulted in a magnitude of data describing student behaviours in the online space. Alongside this shift, student attrition and academic performance has become a profound concern of universities, resulting in dedicated efforts from researchers to understand student engagement with the LMS (Tinto, 1999). Many researchers have used student online behaviours as predictor variables of academic performance (Baker & Yacef, 2009; Seidel & Kutieleh, 2017). However, these have led to diverse and inconsistent results, making it difficult to conclude which digital learning behaviours contribute to academic performance (Conjin et al., 2016).

AIM:

In this study, we aimed to identify the determinants of student engagement using LMS data to predict students at-risk of poor academic performance.

METHOD:

We have analysed data from 518 Biomedical Science (BMS) students at Monash University from six blended units, in which we aimed to determine the online learning behaviours that robustly predict academic performance (unit results) through a linear regression analysis. A cluster analysis was conducted to categorise students into separate groups to identify distinguishing characteristics.

FINDINGS:

We demonstrate that online lecture viewing is the only statistically significant student behaviour contributing to academic performance. Following this study, we aim to analyse 545 BMS at Monash University from a second-year physiology unit, with the aim of generating weekly cluster analyses spanning the twelve weeks of semester.

Knowing the ever-changing work and study demands of students, our findings demonstrate the utility of generating weekly profiles of student engagement (using LMS data) in the tailored design and delivery of student-centric course material.

IMPLICATIONS:

Academics will be able to identify students disengaging with content, allowing support to be provided.

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