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STUDENT PARTICIPATION IN COMPUTING STUDIES TO UNDERSTAND ENGAGEMENT AND GRADE OUTCOME

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ABSTRACT

Aim/Purpose	This paper focuses on understanding undergraduate computing student-learning behaviour through reviewing their online activity in a university online learning management system (LMS), along with their grade outcome, across three subjects. A specific focus is on the activity of students who failed the computing subjects.
Background	Between 2008 and 2020 there has been a multiplicative growth and adoption of Learning Analytics (LA) by education institutions across many countries. Insights gained through LA can result in actionable implementations at higher institutions for the benefit of students, including refinement of curriculum and assessment regimes, teacher reflection, and more targeted course offerings.
Methodology	To understand student activity, this study utilised a quantitative approach to analyse LMS activity and grade outcome data drawn from three undergraduate computing subjects. Data analysis focused on presenting counts and averages to show an understanding of student activity.
Contribution	This paper contributes a practical approach towards LA use in higher education, demonstrating how a review of student activity can impact the learning design of the computing subjects. In addition, this study has provided a focus on poor performing students so that future offerings of the computing subjects can support students who are at risk of failure.

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Findings	The study found that: • Collecting data relating to student activity and analysing the activity is an important indicator of engagement, with cross referencing the data to grade outcome providing information to support modification to the learning design of the computing subjects. • The computing subjects in this study all had the majority of the assessment marks awarded at the later part of the study period. • Students that fail subjects are active within the LMS for the period of the subject even when they submit no assessments • Assessment weight and the time of delivery could influence the outcomes
Recommendations for Practitioners	The collection and analysis of student activity in the LMS can enable learning designers and practitioners to better reflect the subject design and delivery to provide more informed ways of delivering the learning material.
Recommendations for Researchers	Collecting LA requires a thought-out process, designed well in advance of the teaching period. This study provides useful insight that can impact other researchers in the collection of assessment related analytics.
Impact on Society	The cost of education is expensive to those that undertake it. Failing, although expected, potentially can be reduced by examining how education is designed, delivered, and assessed. The study has shown how information on how students are engaging has the potential to impact their outcomes.
Future Research	Further work is needed to investigate whether intervention may assist the poor performing students to improve their grade outcomes relative to activity levels, subsequently impacting their retention.
Keywords	learning analytics, higher education, retention, computing, information technology, learning management system

INTRODUCTION

Since its official inception at the first Learning Analytics & Knowledge conference (LAK) in 2011, the field of Learning Analytics (LA) has been widely adopted in the educational sector as a means of better understanding the higher education student experience. Even though it is still an emerging field, LA has already seen a plethora of trends and paradigm shifts and has been proved to have many benefits (Avella et al., 2016; Buckingham Shum & Crick, 2016) for all stakeholders including students, educators, researchers, institutions, and government agencies (Leitner et al., 2017; Peña-Ayala, 2018). Rienties et al. (2020) defined LA as one of four approaches to understanding teaching and learning using technology, defining it as research into the challenges of collecting, analysing, and reporting data with the goal to improve learning processes. This differs from machine learning and artificial intelligence approaches that seek to understand and predict elements of the student experience, with LA focusing on more holistic approaches (Rienties et al., 2020).

Higher education institutions rely heavily on learning management systems (LMS) to deliver and manage the learning material and associated activities, both from the educator's and the student's perspective. Lectures, assessments, discussions, progress, resources, links, and more are provided with the intent that students will engage within the LMS. LA is one of many approaches to understand the learning patterns of higher education students, with data drawn from student activity that occurs on the institutions LMS. In the current COVID-19 environment students are relying even more heavily on the LMS, with many classes now run entirely online. Understanding how students are using the learning resources available and whether LMS use affects their learning outcomes enables educators to improve the learning experience, and as a consequence student's ability to progress in the studies. Montoro et al. (2019) evidence that minimal research in the use of LA to understand the design of learning resources has been conducted, highlighting missed opportunities for higher education institutions to best understand the student experience.

This study represents the first phase of data analysis to understand undergraduate student-learning behaviour through reviewing their activity in a university online LMS across three computing subjects. Activity from the LMS has been cross-referenced to grade outcome to enable a reflective approach towards determining what impacts student outcome. A focus on poor-performing students (those who failed the subjects) was made during analysis, describing the teaching activities they access, and when they access them, during their studies.

LITERATURE REVIEW

There are many motivations and objectives for implementing LA in higher education (Leitner et al., 2017). The most common motivation being for improved student retention (Friðriksdóttir & Arnbjörnsdóttir, 2017; Minović et al., 2015) with learning and teaching support gaining more relevance over the past few years (Viberg et al., 2018). Insights gained through LA can result in actionable implementations at higher institutions for the benefit of students, including refinement of curriculum, instructor performance, and more targeted course offerings (Avella et al., 2016). Effect on student performance and behaviour has also been of focus. Predictive methods like regression and classification, relationship mining, visualization, and statistics (Avella et al., 2016; Friðriksdóttir & Arnbjörnsdóttir, 2017; Hooda & Rana, 2020; Shih et al., 2011) are but a few, along with experimental methods such as gamification (Moridis & Economides, 2009; Nghe & Schmidt-Thieme, 2015; Romero-Zaldivar et al., 2012; Venkatachalapathy et al., 2017) and social learning analysis (Hooda & Rana, 2020).

LA can also focus on assessment outcomes to inform student progress. Ellis (2013) noted that assessment outcomes have a significant impact on student motivation, with assessment analytics suggested as an important point of focus. Assessment analytics can enable both student and teacher reflection on progress, with teachers being able to reflect on the outcomes in relation to how the learning design may be changed in future offerings of a subject (Ellis, 2013; Sergis & Sampson, 2017). Interestingly, Sergis and Sampson (2017) argued that the reflection phase of interpreting LA is not well reported in the literature, with more ad-hoc interpretations observed. In relation to teamwork, learning analytics can play a critical role in helping moderate student effort (Fidalgo-Blanco et al., 2015).

Educational Data Mining (EDM) supports the teaching and learning in higher education by providing "actionable intelligence" for customization, tutoring and intervention within the learning environment (Leitner et al., 2017). When applied to large data sets related to students' behaviours and actions, EDM promotes the extraction of hidden knowledge, pattern discovery, and predictive modelling (Hung et al., 2012). Over the last two decades the use of LA in higher education has increased dramatically due to the use of Virtual Learning Environments (VLEs) and/or LMS to provide the core interaction for the student cohort (Papamitsiou & Economides, 2014; Pardos et al., 2013). In this context learning analytics is the combination of big data, the learning environment, and analytic techniques with a defined objective to impact upon the student experience (Viberg et al., 2018). For example, Macfadyen and Dawson (2010) have used online activities (emails and discussion messages) to determine student achievements to help generate an informative dashboard for teaching staff. For instructors, the visualisation and calls to action via the dashboard generated with real-time information from learning resources resulted in intervention strategies, proactively reducing opportunities for student disengagement (Pardos et al., 2013). In another example, Shih et al. (2011) linked 'bottom-out' hints with students' eagerness to reveal this information. Effect and student actions were also the focus as Nghe and Schmidt-Thieme (2015) who explored 'personalized forecasting' using historical data to consider the 'student' and 'task' effects.

More recent methods for LA include machine learning (ML) (Sharma et al., 2019) and deep learning (DL) (Ahad et al., 2018). Such methods are well suited for the discovery of insights embedded within large and/or diverse data sets, or to build predictive models of student outcomes such as whether they are at risk of failing a subject (Akçapınar et al., 2019). One caveat recognised however is in how ML is utilised, with researchers tending to treat ML methods as a "black-box": input data is fed in, insights are output, and understanding or explanation provided of how the outcomes came about is omitted or lacking (Sharma et al., 2019). Such an approach limits the reproducibility of the results or efficacy by others and limits the amount of insights acquirable due to the lack of "context" in their approach. Work by Sharma et al. (2019) strives to begin from a theory and context foundation when extracting the feature data that is input into ML algorithms (titled a "grey-box" approach) to alleviate the issues associated with the "block-box" approach. Nonetheless, an advantage of utilising ML (or DL) over other LA methods is its easier inclusion of diverse data sets from a variety of sources beyond LMS, and for building predictive models. For example, student-centric metrics such as eye tracking and physiological metrics can also be considered (Sharma et al., 2019), or collating usage metrics of additional learning apparatus such as VR headsets (Christopoulos et al., 2020). Akçapınar et al. (2019) built a predictive classifier that could by week 3 accurately classify 20 out of 27 students that would fail the subject. Ahad et al. (2018) considered the "how, when and why" learning was taking place through the proposal of a framework that utilises DL to analyse highly diverse data collected through an installation of Internet of Everything (IoE) infrastructure at learning institutions. Sensors worn by students can collect activity movements and patterns, location tracking, and class attendance, while sensors installed at learning locations (e.g., classrooms and laboratories) can track environmental metrics such as temperature, light sources, and humidity. The use of such auxiliary data from sources beyond those collected by LMS has supporting evidence. Broadbent (2016) found that the inclusion of physiological factors such as self-efficacy and motivation can play a more weighted role in the prediction of student learning outcomes over LMS collected data.

The use of LA has enabled a move away from Grade Point Average (GPA) to measure success to consider the affective state of students at varying times by using ML to adjust the learning experience as necessary (Nghe & Schmidt-Thieme, 2015). Knoop-van Campen and Molenaar (2020) used dashboards informed by student activity to provide task, process, or personal feedback. In combination with teacher-prompted and student-prompted feedback, students received a variety of feedback forms to support them at various stages of their learning. Also using a dashboard, Lavoué et al. (2017) presented an approach for assessing a student's emotional state during a learning experience, highlighting that emotions can have a strong impact on the learning process and student's self-regulation. Derick et al. (2017) used visualisations to present emotional state in a learning analytic dashboard with mixed results. Mangaroska et al. (2021) extended the collection of analytic data to include wearable sensors as a form of multimodal data to understand student behaviour, arguing that the combination of data sources provides a more effective and ethical approach to providing student facing LA innovations.

LA allows institutions to (1) better understand what, and how, factors (e.g., LMS activity levels) correlate with student outcomes, and (2) by utilising such factors one can develop predictive models about future student cohorts. A common use of predictive models is the early identification of students at risk (Akçapınar et al., 2019; Herodotou et al., 2020). With at risk students identified early in the teaching term, it allows institutions to instigate support-focused interventions. In work by Herodotou et al. (2020), their Student Probabilities Model was implemented alongside motivational-focused interventions: the targeted communication to such students via text, email, or phone. They concluded that their intervention program resulted in a notable uptick of student retention and learning outcomes. While ML has been demonstrated as a particularly effective tool for developing predictive models, with the plethora of ML algorithms to choose there is ongoing work that remains to compare and assess their suitability (Chen & Cui, 2020).

Within the field of EDM, Gasevic et al. (2016) and Jones (2019) noted some major questions about the use of LA in education such as ownership and protection of personal data, data sharing and access, and ethical use of data. Ethical challenges remain a concern for the effective use of LA going forward (Ferguson, 2019), with efforts such as those by Sclater (2016) to develop a code of practice being a step in the right direction. In any situation where LA is to be considered, these questions need to be considered at the forefront of learning design. The utilisation by LA by education institutions coincides with questions about the consent (or lack of) students have provided for their data to be analysed, and their behaviours/outcomes probed. Hooda and Rana (2020), through their systematic review of the field, identify ethics, data protection, and privacy as key future directions to be addressed, noting that as the data available for LA continues to expand, so do the privacy and ethics concerns. Furthermore, some institutions may share their datasets with others, or submit them to data sharing repositories (Jones, 2019), further exasperating the concerns. Jones (2019) reflects on the consequences of students losing the ability to govern their data, stating that "lives become more transparent to those with the data while their data practices grow more opaque and influential." Furthermore, they question whether LA encroaches on students' autonomy, particularly where LA is utilised with the objective to create predictive models and thus be used to 'interfere' when a student for example may be identified as at risk. Proposals such as the DELICATE framework attempt to formalise best practices for how researchers and institutions should approach LA in respect to data collection and analysis, with an emphasis on involving the students into the equation (Corrin et al., 2019).

As introduced, the goal of this study was to review student activity collected from the LMS to determine if the information has the potential to provide the foundation for a methodology to employ data analytics within the education context to enhance the development, delivery, and execution of undergraduate education via a LMS. This study represents the first phase of the data analysis primarily to determine if this approach has potential for both simple statistical analysis and to determine if the data could be used to provide the foundation for a data driven predictive approach using data mining tools. For this study the focus was narrowed to examine those students who received a failing grade in their studies and to examine how at risk students use the LMS. It is assumed that at risk students will have a low rate of engagement within the LMS and their activity will be higher in the early stages of the subjects. The study's aim is to examine if data analytics can provide insights into the behaviour of this cohort to determine if the assumptions are correct and to examine how the learning design implemented at the study institution may influence the activity of students within the LMS. To help understand the context in which the data is drawn, the next section describes the teaching and learning situation presented in this study.

Description of the Teaching and Learning Situation

Three undergraduate computing subjects from Deakin University in Australia were selected to provide insights into the daily activities that students undertake over a semester of study. Each subject is included in the Bachelor of Information Technology degree, with student activity in the LMS drawn from both face-to-face on campus and via the cloud. Each subject is conducted over 14 weeks: 11 weeks of teaching and assessment, 3 weeks for study and exams (if included in the subject). Students are able to withdraw from their studies prior to week 4 without financial commitment. The subjects selected were:

Subject 1: A programming for engineers subject: A core first year subject conducted in the second semester that focuses on the basics of computer programming using tools and languages that engineers are likely to use. To be eligible to pass in this subject, students must achieve a mark of at least 50% overall. This subject included a 50% final exam as a part of the assessment regime.

Subject 2: A discrete mathematics subject: A core first year, second semester subject that explores the foundations of discrete mathematics. The basis for mathematical reasoning in applied and computational sciences. The subject is designed to prepare students for further study in disciplines where discrete mathematics play a fundamental or foundational role: cryptography, networks, computer programming and analysis of algorithms. This subject included a 60% exam as a part of the assessment regime. To be eligible to pass this subject, students must achieve a mark of at least 50% overall and achieve at least 40% in the final exam.

Subject 3: A networking subject: A core second year, second semester subject that explores the current state of computer networks, reviewing the types of networks in use today. The subject also focuses on the communication protocols used and their arrangement into modular stacks, how problems are solved using networks and protocols, and an exploration of common network security issues. To be eligible to pass in this subject, students must achieve a mark of at least 50% overall. This subject included a 60% final exam as a part of the assessment regime.

Table 1 outlines the assessment profile of the each of the subjects and defines the number of assessments in each subject, as well as the weight (indicated by the shading) and week the assessments were due for each subject.

Table 1. Assessment profile of the computing subjects

Subject 1			10%			10%		15%					15%	50%
Subject 2			2%	2%	2%	12%	2%	2%	2%	2%	12%	2%		60%
Subject 3					15%				15%		10%			60%
Week	0	1	2	3	4	5	6	7	8	9	10	11	12	13

Subjects selected for the study were chosen based on the assessment design primarily to provide the opportunity to examine whether the design has an impact on the activity of study behaviour during the study period. Subject 1 starts assessments early and has a consistent schedule and weighting to the assessment. Subject 2 also starts assessment early but maintains a very consistent schedule but assigns low weights to many of the assessment tasks. Subject 3 maintains a schedule similar to subject 1 albeit the assessment begins later within the 14-week period. All subjects have heavily weighted assessment task at the end of the 14 weeks.

METHODOLOGY

To evaluate the data acquired from the three computing subjects at Deakin University, this study employed a quantitative approach with statistical analysis to present the analytics of student use of the LMS. Deakin University uses an (online) web-based LMS to deliver learning resources, administer the student cohort, facilitate student communication, and allow students to submit assessments. A LMS is simply a web-based application that provides links to information. These links can be captured using tools such as Google Analytics and the information refined to provide a comprehensive account of the activities of individual students throughout their engagement within the LMS. To collect the data from the LMS, Google Analytics was collected from June to November 2018 across the three subjects described above. Each individual link selected in the LMS from each student was collected and recorded within a database. Google Analytics data consists of basic information relating to the date and time a link was selected, the actual URL of the links, and other information relating to the user identification and the environments used. The information in this form does not provide a lot of value other than to record access logs of students. In order to better understand what each link related to, a tool was developed to visit and extract the title and metadata of each of the rendered pages. This information enables the identification of the type of resource the link related to. The resulting dataset then underwent a series of refinements to add value to the information and was organised within a SQL relational database to enable simple and complex queries to be executed to extract a variety of information for analysis. The resulting data collected consisted of subject code, record ID (substitute for student ID), title of the URL visited, the metadata from each URL visited, and date and time of the activity. This information was then used to identify the type of activity the student engaged with. Based on the title and metadata, each URL was classified into one of the following activity types by the study researchers, with classification confirmed by the teacher staff of each of the computing subjects (duel stage confirmation of classification):

- **R = Resource**: Any information relating to the subjects learning material such as weekly learning guides, reading, practical activities, practical solutions, links, videos, lecture slides, and recordings.
- **A = Assessment activity**: A resource that defined an assessment task or provided help and guidance relating to the assessments. Assignment descriptions are generally available at the beginning of the subject but not in all cases.
- **D = Discussion:** Any interactions with the discussion forums including posting, reading, and responding to messages.
- **P = Progress:** Any links that provide information relating to the students' progress, grades, quiz results, and calendar notifications.
- **S = Submission:** Any links that relate to the submission of an assessment file, record, update via the online submission tool.

Finally, each date of the URL was classified according to the week in which the interaction took place according to the 2018 teaching period. Given that the students have access one week prior to the start of the semester, weeks start at 0 and continue to the end of the exam period in week 14. In total 4,736,835 individual links were collected, analysed, and classified. Links that were generated by staff or were not related to the LMS and the published artefacts or tools were excluded from the dataset.

In addition to the LA data, grade outcomes for each assessment task and the final grade for students in each subject was also collected and included in the dataset. The resulting data enabled the identification of students achieving a particular grade and all the associated activity undertaken by the student for the 14 weeks recorded. In total 1,063 student records were available for analysis, with 280 from subject 1, 245 from subject 2, and 538 from subject 3.

The data for this study has been made publicly available via a self-hosted online portal at the research institution (Deakin University). The data can be accessed by the URL: https://vhost2012.hosted-sites.deakin.edu.au and downloaded as raw data in the form of SQL or queried via a purpose-built online query tool. A data use agreement is provided on the hosting webpage, where any publications that uses the dataset or results derived from the dataset must acknowledge the source and authors via citations within the published documents.

To gain an initial overview of the data, it was extracted and grouped based on the activity, subject, week, and grade level. This study is the first phase of the analysis of the dataset. The methodology selected is designed to provide an overview of the data and to identify opportunities to further analyse the data using statistics and data mining methods. Being the first phase of analysis, machine learning techniques were not utilised at this stage however may be considered in future iterations. Additionally, machine learning can often be seen as a "black-box" during its use, limiting the amount of understanding or explanation to explain its results (Sharma et al., 2019). A more fine-grained approach to analysis through statistical analysis potentially provides a more context-based understanding of the students' behaviours from the data available.

Given each subject has a different number of students, averages were calculated to enable each subject to be compared. For this study only activity data relating to the failing grades was extracted and used. Overall, a total of 655,209 (13.8%) of the 4,736,835 links were examined for students who received a failing grade. 42,347 records related to the XN grade and 612,862 related to the N grade. When a student fails a subject at Deakin University they will receive an XN or N grade. An XN grade is assigned where the student receives no actual assessment outcome and implies that they did not submit an assessment task or sit an exam or associated test. An N grade is assigned where the student's final grade is less than 50 out of 100 or they failed to meet a subject's assessment hurdle. Given that an N grade could range from 1 to 49 out of 100, the data has been reclassified to enable three N levels to improve the analysis of those students just failing to those failing badly. Within the study the following are used to define the N grade level:

- XN: No Assessments completed OR 0 grade outcome achieved
- NL (Low Fail): > 0 to <= 30 out of 100 overall
- NM (Medium Fail): > 30 to <= 44 out of 100 overall
- NH (High Fail): > 44 to < 50 out of 100 overall

Students that receive a NL, NM, or NH grade are either not submitting all the assessment tasks or the assessments submitted are of a low standard. These ranges provide an opportunity to examine the activity levels in greater detail. It is assumed that there will be a different level of activity within these ranges that would not be identifiable if they remained in a single group.

To guide this study and ensure appropriate ethical practices as described in Ferguson (2019) and Sclater (2016), this study received ethics approval through Deakin University's ethics committee, approval code: STEC-43-2017-MCKENZIE. Any students who had opted to be withdrawn from the study had their activity removed. Each student record was provided with a unique code to remove any potential connection to personal data. This unique code was applied across all three subjects to potentially cross reference student participation.

RESULTS AND DISCUSSION

To present the results into study activity and grade outcome from the computing subjects, the following results are organised into two sections. The first section provides an overview of the grade outcome and activity data across the three computing subjects that are the focus on this study. The second section examines the activities for each grade outcomes for each subject for each week. Further analysis of the results is shown in the appendix, demonstrating the activity profiles for all grades for each activity type.

SECTION 1: OVERVIEW OF GRADE OUTCOME AND ACTIVITY DATA

Table 2 defines the distribution of the number of students across the final grade outcomes for each subject included in this study. In all cases the majority of students achieved a NL grade and those in the just fail category or NH constitutes the smallest group. This indicates that students that fail are failing badly.

Table 2. Grade outcome for the computing subject

Subject	**1**	**1**	**1**	**1**	**2**	**2**	**2**	**2**	**3**	**3**	**3**	**3**
Grade	XN	NL	NM	NH	XN	NL	NM	NH	XN	NL	NM	NH
Count	**20**	**29**	**24**	**7**	**21**	**30**	**15**	**17**	**23**	**45**	**37**	**15**
%	7.1	10.4	8.6	2.5	8.6	12.2	6.1	6.9	4.3	8.4	6.9	2.8

Tables 3, 4, and 5 provide an indication of where the failing grades sit within the whole subject. Grade P represents a passing grade through to HD being the highest grade a student can achieve. Table 3 defines the distributions (%) of students that achieved a particular grade. Table 4 defines the distribution of activity across each grade. It is expected that the more students within a particular grade group will result in a similar distribution of activity for the corresponding grade. This is the case for all subjects and grades except the D grade group where there is a slight difference between subject 1 and 2.

Table 3. Grade distribution for each subject

	Grade							
Subject	**XN**	**NL**	**NM**	**NH**	**P**	**C**	**D**	**HD**
1	7.1	10.4	8.6	2.5	16.1	16.8	16.8	21.4
2	8.6	12.2	6.1	6.9	15.5	19.2	13.1	18.4
3	4.3	8.4	6.9	2.8	20.8	25.7	19.3	11.9

Table 4. Activity distribution for each subject

	Grade							
Subject	**XN**	**NL**	**NM**	**NH**	**P**	**C**	**D**	**HD**
1	1.5	5.0	6.9	3.6	15.7	17.5	17.9	31.8
2	1.2	5.1	4.3	5.3	14.4	26.0	17.1	26.5
3	0.5	2.1	4.4	4.5	16.7	25.3	27.0	19.5

Table 5 defines the average number of links visited for each grade group for each subject.

Table 5. Activity proportional to students

	Grade							
Subject	**XN**	**NL**	**NM**	**NH**	**P**	**C**	**D**	**HD**
1	64.2	205.8	287.6	149.8	653.0	725.5	743.5	1320.7
2	55.5	239.9	202.6	246.6	672.4	1210.8	795.9	1236.3
3	22.2	207.8	210.3	99.4	787.5	1193.4	1270.7	917.5

It is clear that the more activity there is, the higher the grade, but it is not possible to predict a particular grade simply by examining the level of activity a student makes within the LMS. In all cases the level of activity for those students failing is a third or more less than those passing or receiving a P grade or above. Focusing on the failing grades, students receiving an XN clearly have less engagement but for those that received a NH or just failed the level of activity does not appear to increase despite these students being closer to a passing grade. With the assessment profile of each subject in mind, there is a slight difference for subject 2 that has a weekly assessment task scheduled. Overall, the activity data can be used to identify possible at risk students, however this should not be used exclusively to predict grade outcome.

Section 2: Grade Level Activity

As described by Romero-Zaldivar et al. (2012) the implementation and outcomes of LA is impacted by the particular LMS and institutional teaching and learning approach. In order to gain a better understanding of the type of activities failing students are engaged with and whether assessment profiles influence activity, Tables 6, 7, 8, and 9 display the number of links visited for each activity per week of the subject relative to the number of students that achieved the specified grade. For instance, in Table 6 for subject 1, resources (R), Week 0 indicates an average of 2 links were visited for this activity type for each student in the XN grade range. It should also be noted that the D (discussion) activity will depend greatly on the number of discussion posts per subject, therefore a high number may be due to the subject having many more discussion posts than another subject.

Assessments due for each subject have been indicated by shading the relative week. The actual due dates may vary from those indicated as extensions may have been granted to some or all students. Each table defines the average links visited by students that received an XN, NL, NH or NH grade.

Table 6: XN student activity

Subject	1	1	1	1	1	Subject	2	2	2	2	2	Subject	3	3	3	3	3
Week	R	A	D	S	P	Week	R	A	D	S	P	Week	R	A	D	S	P
0	2	6	5	2	2	0	7	0	0	1	0	0	2	0	11	1	7
1	53	16	15	23	10	1	19	0	1	1	2	1	54	2	16	4	39
2	24	10	15	19	4	2	14	0	1	0	5	2	22	3	3	2	9
3	20	64	17	20	6	3	6	0	3	1	8	3	18	0	12	1	5
4	9	6	9	10	12	4	10	0	2	1	7	4	16	17	10	5	30
5	80	66	14	30	21	5	12	0	1	0	7	5	14	2	3	3	16
6	4	0	3	6	5	6	44	1	108	6	22	6	1	4	0	2	5
7	5	3	10	9	7	7	30	3	39	6	24	7	0	0	0	0	1
8	66	11	28	18	4	8	44	4	6	11	21	8	49	16	21	5	22
9	16	23	17	14	10	9	12	0	13	0	6	9	20	2	13	2	8
10	0	0	0	1	1	10	7	0	3	4	13	10	0	0	0	0	1
11	3	1	1	3	2	11	1	0	1	2	4	11	0	0	0	1	2
12	0	0	0	1	1	12	27	1	12	3	13	12	1	0	2	0	1
13	5	0	13	3	1	13	5	0	2	0	0	13	1	0	0	0	7

It was expected the activity profile for the XN grade would show initial activity across all activity types at the start of the subject then drop away as the subject progresses. Across the subjects, Table 6 shows that activity drops away around week 9 onwards, with the exception of subject 2 that continues to show some activity. It is assumed this is due to the different assessment profile compared to subjects 1 and 3. Given that students with a failing grade level do not generally submit any assessment tasks, it was expected that very little activity relating to the assessment (A) and submissions (S) would be present, especially in the later stages of the subject. The data indicates activity throughout the 14 weeks, particularly around the assessment due dates across all activities. Activity peaks around week 8 then tapers off as the exam approaches. The data indicates students are not only accessing the learning resources (R) but also reviewing the assessment material, submitting assessments (A), reading discussions (D), and even accessing links relating to their progress (P). The data implies students are active but unable to engage to a level that leads to learning and the completion of any valid assessment outcomes.

Table 7 shows the average links visited by students that received an NL grade. Noted is that in many cases, students within this grade level do not sit the final exam. As with the XN students, activity is present throughout the 14 weeks and in all cases is higher around the assessment due dates except where the assessment's weighting was low as seen in subject 2 where weekly assessments worth 2% and 10% were scheduled. This indicates that regular assessment tasks that do not contribute a lot to the final result do not encourage students to engage. Most of the assessment activity for subject 2 was prior to the final exam worth 60%, indicating that for this subject many students hoped to pass by completing the final exam. In all subjects activity prior to the exam indicates students were preparing for the final exam. Given that the exam assessment is worth 50%-60% of the overall mark across the subjects in this study, it is likely that students felt that they had an opportunity to pass but as experience indicates, a lack of engagement early in the learning makes it very difficult complete a final exam where the entire subject content is examined. In comparison to the XN grade, the NL grades students have a higher level of activity throughout the 14-week period across all activities.

Table 7: NL student activity

Subject	1	1	1	1	1	Subject	2	2	2	2	2	Subject	3	3	3	3	3
Week	R	A	D	S	P	Week	R	A	D	S	P	Week	R	A	D	S	P
0	6	8	13	8	3	0	19	0	5	3	12	0	10	0	4	1	8
1	57	48	26	28	6	1	58	0	12	7	19	1	84	4	14	7	38
2	62	73	70	39	25	2	25	0	3	2	29	2	83	5	23	10	36
3	73	64	74	40	23	3	75	1	21	11	57	3	119	48	15	14	76
4	12	14	14	13	15	4	90	0	12	15	48	4	143	112	106	32	133
5	74	48	87	51	53	5	55	0	13	4	45	5	37	8	16	8	47
6	28	4	10	12	6	6	133	1	29	9	52	6	24	2	10	3	24
7	17	2	15	9	9	7	105	0	24	8	60	7	25	8	12	8	44
8	33	18	18	15	16	8	29	0	11	4	31	8	100	76	130	18	98
9	43	43	39	32	21	9	52	1	6	3	27	9	41	10	43	6	33
10	13	2	4	5	3	10	60	1	14	24	34	10	30	50	46	12	48
11	60	12	47	32	20	11	27	3	5	23	22	11	44	6	21	3	41
12	22	0	9	12	18	12	134	28	48	7	26	12	79	2	13	3	44
13	96	1	36	34	12	13	91	41	21	3	7	13	27	0	19	2	22

Tables 8 and 9 show the average links visited by students that received an NM or NH grade. As with the XN and NL grades, activity is present across all activity types for the 14 weeks albeit higher than the lower grade groups. Activity is higher around the assessment due dates especially for subjects 1 and 3. The regular assessment profile for subject 2 does appear to be influencing the level of activity over the entire 13 weeks compared to the other subjects as indicated by the level of activities relating to the gathering of information such as activity R and D but the activity associated with assessments (A) is very low indicating the students are simply not engaging in this space until the end of the subject as the final exam worth 60% approaches. Similar activity is shown in the Appendix Tables A1, A2, A3, A4, and A5 with activity types that relate to each resource type shown. The assessment profile of subjects 1 and 3 shows 10 to 15% assessment tasks at regular intervals throughout the study period. The data clearly indicates that this generates activity across all the activities. The weighting of the final exam of 50 to 60% means the majority of the marks are not gained until the end of the subject.

Table 8. NM student activity

Subject	1	1	1	1	1	Subject	2	2	2	2	2	Subject	3	3	3	3	3
Week	R	A	D	S	P	Week	R	A	D	S	P	Week	R	A	D	S	P
0	28	25	20	8	8	0	17	0	14	3	17	0	6	0	6	1	4
1	132	52	64	28	21	1	48	1	7	4	21	1	93	4	26	5	34
2	99	104	64	39	20	2	33	0	5	1	26	2	91	13	24	9	42
3	58	44	27	40	15	3	136	2	10	5	73	3	126	30	21	18	69
4	31	17	16	13	14	4	80	0	11	3	79	4	238	108	139	29	153
5	170	73	129	51	53	5	82	0	2	3	47	5	52	15	5	11	59
6	79	12	8	12	16	6	188	2	37	31	97	6	31	8	4	6	42
7	40	12	35	9	15	7	158	4	29	12	73	7	33	18	17	8	37
8	75	43	45	15	31	8	79	6	15	7	59	8	142	62	122	24	121
9	74	57	68	32	27	9	86	8	9	41	56	9	16	26	14	7	43
10	48	4	23	5	15	10	86	13	25	85	90	10	70	57	70	13	92
11	95	28	67	32	29	11	121	14	15	33	63	11	39	13	17	7	87
12	66	3	36	12	19	12	231	96	57	10	44	12	105	0	29	4	70
13	246	2	90	34	20	13	274	76	38	8	13	13	87	0	21	2	46

Table 9. NH student activity

Subject	1	1	1	1	1	Subject	2	2	2	2	2	Subject	3	3	3	3	3
Week	R	A	D	S	P	Week	R	A	D	S	P	Week	R	A	D	S	P
0	8	1	4	6	0	0	23	0	3	2	13	0	19	0	3	1	10
1	89	51	50	61	12	1	75	0	22	6	9	1	101	1	4	7	39
2	269	186	336	121	39	2	25	0	6	3	23	2	104	3	9	6	40
3	164	53	108	50	48	3	159	2	12	15	91	3	140	18	50	21	74
4	44	19	54	19	21	4	197	0	18	13	78	4	168	145	72	47	237
5	346	176	433	126	53	5	109	0	11	13	63	5	53	46	8	13	86
6	8	1	10	7	8	6	221	2	49	16	160	6	32	14	0	14	75
7	34	6	22	20	12	7	66	1	5	12	61	7	35	15	22	8	56
8	102	58	83	95	22	8	68	0	3	20	63	8	56	89	45	27	173
9	173	168	469	99	42	9	140	0	13	21	67	9	57	20	2	10	38
10	12	3	163	11	11	10	95	1	5	70	75	10	57	41	18	23	95
11	129	23	99	54	10	11	120	60	21	36	84	11	153	7	31	10	136
12	162	1	41	61	30	12	238	66	46	32	58	12	299	8	50	13	136
13	426	1	133	110	18	13	200	56	65	13	31	13	85	0	10	3	55

In this study, the computing subjects were designed with an assumption that students engage weekly within the LMS to achieve the learning activities. The results have demonstrated that students who receive an N grade attempt most of the assessment tasks during the teaching period, but do poorly most likely due to a lack of engagement in the learning process and are therefore poorly equipped to complete the assessment to an acceptable standard. Such findings complement the existing consensus that students that are more active and engaged generally perform better than lesser engaged or active students, even for subjects besides computing subjects (Hung et al., 2012). However, as Joyce et al. (2018) suggested, assignments are also impacted by teaching quality and the intellectual rigor present in the learning environments. Assessment analytics can however enable both student and teacher reflection on progress, with teachers in particular being able to reflect on the outcomes in relation to how the learning design may be changed in future offerings of a subject (Ellis, 2013; Sergis & Sampson, 2017). In this paper, analytic outcomes could be used to drive teacher reflection on the learning design. Future offerings of the three computing subjects as presented in this paper may focus less on the final exam as a large component of the assessment regime. Overall, the outcomes of student activity should be used in conjunction with other academic judgement to inform the design of assessments related to these computing subjects and to improve student retention.

LIMITATIONS

This study prioritised its analysis towards students who have failed their subjects, and only included to a lesser extent passing students. A closer analysis of this group in a similar fashion to the failing students may provide further insights not currently included in this study.

Lastly, this study focused on students from three computing subjects only, thus the applicability of our results to non-computing cohorts perhaps cannot be automatically assumed.

CONCLUSION

Using LA in higher education can result in actionable implementation for the benefit of students (Avella et al., 2016). Assessment analytics in particular can enable both student and teacher reflection on progress, with teachers being able to reflect on the outcomes in relation to how the learning design may be changed in future offerings of a subject (Ellis, 2013; Sergis & Sampson, 2017). In this study, a focus on the student activity in computing subjects, with a particular focus on students at risk, has highlighted opportunities for updates to the learning design, specifically with regard to the assessment structure and due dates. Across each subject, student activity is varied based on the week. In all three subjects the assessment was different both in the distribution of the assessment due dates and the value of the assessment tasks. The assessment design informs the way in which students engage with a subject, subsequently shown by the activity as reported in this paper. Of significance is that, despite receiving poor outcomes, both XN and N students continued to report activity on the LMS throughout the teaching period, through to the exam period. While a drop-off of activity is expected around week 4 of the teaching period (due to internal dates of student withdrawal from subjects), the results here suggest that students are maintaining their involvement in the subject and reporting activity throughout the trimester. In all subjects the activity reflected the timing of the assessment tasks but not where the assessment weighting was low. Assessment strategies where more frequent assessment is conducted do not result in higher engagement in the LMS. This was reflected in subject 2 where weekly tests were conducted. Activity was low until the exam in weeks 12 and 13. This indicates that small regular assessments tasks are not encouraging engagement and that assessment tasks that have a higher weighting will attract more activity.

This study represents the first phase of the data analysis primarily to determine if this approach has potential for simple statistical analysis and to determine if the data could be used to provide the foundations for a data driven predictive approach using data mining tools. Further work is required to extend the understanding of student activity and how this can impact grade outcome.

FUTURE WORKS

Further work is needed to investigate whether intervention may assist the poor performing students to improve their grade outcomes relative to activity levels. Along with this, reviewing the activity profile of students across the complete set of grades will provide more insight to determine whether student outcomes are associated with LMS activity. Using the complete data set, other analysis techniques such as machine learning or data mining could be explored to determine if prediction of grade outcome can be achieved based on LMS data.

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APPENDIX

The following tables define the level of activity for a particular resource across all grade ranges for each week. These results provide a profile of all grade levels with each activity type.

Table A1. Resource R student activity

Subject	1	1	1	1	Subject	2	2	2	2	Subject	3	3	3	3
Grade	XN	NL	NM	NH	Grade	XN	NL	NM	NH	Grade	XN	NL	NM	NH
Week	R	R	R	R	Week	R	R	R	R	Week	R	R	R	R
0	2	6	28	8	0	7	19	17	23	0	2	10	6	19
1	53	57	132	89	1	19	58	48	75	1	54	84	93	101
2	24	62	99	269	2	14	25	33	25	2	22	83	91	104
3	20	73	58	164	3	6	75	136	159	3	18	119	126	140
4	9	12	31	44	4	10	90	80	197	4	16	143	238	168
5	80	74	170	346	5	12	55	82	109	5	14	37	52	53
6	4	28	79	8	6	44	133	188	221	6	1	24	31	32
7	5	17	40	34	7	30	105	158	66	7	0	25	33	35
8	66	33	75	102	8	44	29	79	68	8	49	100	142	56
9	16	43	74	173	9	12	52	86	140	9	20	41	16	57
10	0	13	48	12	10	7	60	86	95	10	0	30	70	57
11	3	60	95	129	11	1	27	121	120	11	0	44	39	153
12	0	22	66	162	12	27	134	231	238	12	1	79	105	299
13	5	96	246	426	13	5	91	274	200	13	1	27	87	85

Table A2. Resource D student activity

Subject	1	1	1	1	Subject	2	2	2	2	Subject	3	3	3	3
Grade	XN	NL	NM	NH	Grade	XN	NL	NM	NH	Grade	XN	NL	NM	NH
Week	D	D	D	D	Week	D	D	D	D	Week	D	D	D	D
0	5	13	20	4	0	0	5	14	3	0	11	4	6	3
1	15	26	64	50	1	1	12	7	22	1	16	14	26	4
2	15	70	64	336	2	1	3	5	6	2	3	23	24	9
3	17	74	27	108	3	3	21	10	12	3	12	15	21	50
4	9	14	16	54	4	2	12	11	18	4	10	106	139	72
5	14	87	129	433	5	1	13	2	11	5	3	16	5	8
6	3	10	8	10	6	108	29	37	49	6	0	10	4	0
7	10	15	35	22	7	39	24	29	5	7	0	12	17	22
8	28	18	45	83	8	6	11	15	3	8	21	130	122	45
9	17	39	68	469	9	13	6	9	13	9	13	43	14	2
10	0	4	23	163	10	3	14	25	5	10	0	46	70	18
11	1	47	67	99	11	1	5	15	21	11	0	21	17	31
12	0	9	36	41	12	12	48	57	46	12	2	13	29	50
13	13	36	90	133	13	2	21	38	65	13	0	19	21	10

Table A3. Resource A student activity

Subject	1	1	1	1	Subject	2	2	2	2	Subject	3	3	3	3
Grade	XN	NL	NM	NH	Grade	XN	NL	NM	NH	Grade	XN	NL	NM	NH
Week	A	A	A	A	Week	A	A	A	A	Week	A	A	A	A
0	6	8	25	1	0	0	0	0	0	0	0	0	0	0
1	16	48	52	51	1	0	0	1	0	1	2	4	4	1
2	10	73	104	186	2	0	0	0	0	2	3	5	13	3
3	64	64	44	53	3	0	1	2	2	3	0	48	30	18
4	6	14	17	19	4	0	0	0	0	4	17	112	108	145
5	66	48	73	176	5	0	0	0	0	5	2	8	15	46
6	0	4	12	1	6	1	1	2	2	6	4	2	8	14
7	3	2	12	6	7	3	0	4	1	7	0	8	18	15
8	11	18	43	58	8	4	0	6	0	8	16	76	62	89
9	23	43	57	168	9	0	1	8	0	9	2	10	26	20
10	0	2	4	3	10	0	1	13	1	10	0	50	57	41
11	1	12	28	23	11	0	3	14	60	11	0	6	13	7
12	0	0	3	1	12	1	28	96	66	12	0	2	0	8
13	0	1	2	1	13	0	41	76	56	13	0	0	0	0

Table A4. Resource S student activity

Subject	1	1	1	1	Subject	2	2	2	2	Subject	3	3	3	3
Grade	XN	NL	NM	NH	Grade	XN	NL	NM	NH	Grade	XN	NL	NM	NH
Week	S	S	S	S	Week	S	S	S	S	Week	S	S	S	S
0	2	8	8	6	0	1	3	3	2	0	1	1	1	1
1	23	28	28	61	1	1	7	4	6	1	4	7	5	7
2	19	39	39	121	2	0	2	1	3	2	2	10	9	6
3	20	40	40	50	3	1	11	5	15	3	1	14	18	21
4	10	13	13	19	4	1	15	3	13	4	5	32	29	47
5	30	51	51	126	5	0	4	3	13	5	3	8	11	13
6	6	12	12	7	6	6	9	31	16	6	2	3	6	14
7	9	9	9	20	7	6	8	12	12	7	0	8	8	8
8	18	15	15	95	8	11	4	7	20	8	5	18	24	27
9	14	32	32	99	9	0	3	41	21	9	2	6	7	10
10	1	5	5	11	10	4	24	85	70	10	0	12	13	23
11	3	32	32	54	11	2	23	33	36	11	1	3	7	10
12	1	12	12	61	12	3	7	10	32	12	0	3	4	13
13	3	34	34	110	13	0	3	8	13	13	0	2	2	3

Table A5. Resource P student activity

Subject	1	1	1	1	Subject	2	2	2	2	Subject	3	3	3	3
Grade	XN	NL	NM	NH	Grade	XN	NL	NM	NH	Grade	XN	NL	NM	NH
Week	P	P	P	P	Week	P	P	P	P	Week	P	P	P	P
0	2	3	8	0	0	0	12	17	13	0	7	8	4	10
1	10	6	21	12	1	2	19	21	9	1	39	38	34	39
2	4	25	20	39	2	5	29	26	23	2	9	36	42	40
3	6	23	15	48	3	8	57	73	91	3	5	76	69	74
4	12	15	14	21	4	7	48	79	78	4	30	133	153	237
5	21	53	53	53	5	7	45	47	63	5	16	47	59	86
6	5	6	16	8	6	22	52	97	160	6	5	24	42	75
7	7	9	15	12	7	24	60	73	61	7	1	44	37	56
8	4	16	31	22	8	21	31	59	63	8	22	98	121	173
9	10	21	27	42	9	6	27	56	67	9	8	33	43	38
10	1	3	15	11	10	13	34	90	75	10	1	48	92	95
11	2	20	29	10	11	4	22	63	84	11	2	41	87	136
12	1	18	19	30	12	13	26	44	58	12	1	44	70	136
13	1	12	20	18	13	0	7	13	31	13	7	22	46	55

AUTHORS

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