# Using LMS Records to Track Student Performance: A Case of a Blended Course

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Abstract: This paper explores the use of Learning Management System (LMS) logs to analyse student performance in a blended course. The study aims to identify how LMS data can inform teaching strategies and intervention, focusing on which variables most influence students' performances. The course was designed using Moodle, incorporating programmed learning, conditional activities, and assessments like quizzes, flash tests, and self-assessments.

Data on students' activities, including access logs, quiz scores, and final grades, were collected and analysed. The results show that students with higher LMS activity, particularly those who completed more self-assessments and engaged consistently, tended to perform better. However, while self-assessment activities increased engagement, they had a weaker correlation with final grades compared to midterm exams and flash tests. A strong positive correlation was found between midterm exam performance and final grades, highlighting the importance of these assessments for course success. The study suggests that LMS logs can be a useful tool for teachers to monitor student behaviour and to implement timely interventions to support struggling students.

## 1 INTRODUCTION

The extensive adoption of Learning Management Systems (LMS) in educational institutions has generated vast amounts of data regarding student interactions and behaviors during online and blended courses. These systems record logs of various aspects of student activities, such as the specific resources accessed, the timing of these interactions, and in general, the duration of their engagement with the variety of resources and activities within LMS. As teachers increasingly rely on these systems, the imperative to harness this data for enhancing student learning outcomes becomes very important in teaching practice.

The necessity of using LMS data is underscored by research exploring a deeper understanding of students' learning contexts and behaviors. Ferguson (2012) emphasizes the importance of analyzing these data to optimize learning environments and processes. Ryabov (2012) demonstrates a positive correlation between the overall time logged within an LMS and final academic performance, while Nguyen (2017) finds significant associations between student engagement metrics, such as page views and discussion posts, and learning outcomes. Furthermore, Wei et al. (2015) explored the impact of various online activities on academic success, highlighting the need for teachers to engage with LMS analytics to foster improved student performance. The potential of using such data is also highlighted by studies emphasizing their role in improving retention rates, predicting performance, and identifying students at risk of underachievement (Wong, 2017).

In general, there is a growing need to further contribute to the field of educational data analytics, particularly within the higher education sector, where the effective measurement and improvement of student performance remains a pressing concern (Jha et al., 2019). With that respect, this paper aims to further explore how data recorded in LMS can

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explain student performance by utilizing student logs to pinpoint areas of struggle and help teachers to implement targeted interventions.

## 2 BACKGROUND

Modern educational institutions use different Learning Management Systems (LMS) to support their teaching and learning activities. In recent years, especially in the COVID and post-COVID era the researchers and teachers started to realize the importance of the analysis and use of the LMS generated logs of teachers and students. Since data in log files describe how its users interact and interrelate, the information has been used to create predictive models for different purposes such as foreseeing student performance (Conijn et al., 2017), detecting procrastination (Tuckman, 2005) and clustering students (Cerezo et al., 2016).

According to Gašević et al. (2016) the prediction of students at risk of failing a course and the prediction of students' grades have been based on the data stored in institutional student information systems, trace data recorded by LMSs and other online learning environments; and combinations of different data sources.

Although the LMS logs have emerged as power tools for capturing and analysing student behaviour and the data from LMS has contributed to insights into student learning paths and to predictions about student performance, the use of LMS data for early prediction of student performance is still limited (see Rotelli, Fiorentino & Monreale; 2021; and Baginda, Santoso & Janus; 2022). Tamada et al. (2022) used Machine Learning techniques based on logs from the LMS (Moodle) due to the fact that all interactions in the LMS generate a log, which stores information in a database, the amount of data collected is rapidly increasing in volume and complexity, but also allowing statistical analysis, data mining, and building predictive models of school performance that helps to detect students at risk.

Researching LMS student logs Kadoić & Oreški (2018) found in their study the correlation between the number of logs in the Moodle e-course and the final grades and Felix et al. (2019) found that the number of interactions with the system, attendance, and time spent on the platform were essential variables in predicting student outcomes. Also, Kaensar & Wongnin (2023) study supports the idea that student behaviour in online learning platforms like Moodle affected student performance.

Based on the previous findings this research tries to provide teachers with further analysis of how to use LMS logs to identify possibilities to improve learning design of their blended courses enabling best student performance.

## 3 RESEARCH AIMS AND METHODOLOGY

The main aim of the paper is to explore different ways of using LMS logs to analyse students' activities and describe their behaviour in a blended course.

With that sense, the following research questions are outlined:

1. In what way can student logs be used to analyse students' performance?
2. Which are the variables derived from the LMS records that most influence student performance?
3. How can teachers use LMS analytics/student logs as a predictive techniques/tools (e.g. a teacher can identify areas where students may be struggling and implement targeted interventions to improve student outcomes.)

In the initial phase, the online part of the blended course was developed based on the principles of programmed learning within the LMS Moodle. A range of online resources and knowledge assessments were incorporated, along with conditional activities, to establish a clear learning pathway for students. Additional details regarding the programmed learning principles, conditional activities, and the course overall can be found in the next section.

Data on students, including their final grades were gathered from Moodle by exporting student scores from all quiz activities, including midterms, flash tests, and self-assessment quizzes. Students' engagement was obtained from course activity logs. A Moodle log consists of the time and date it was accessed, the Internet Protocol (IP) address from which it was accessed, the name of the student, each action completed (i.e., view, add, update, or delete), the activities performed in different modules (e.g., the forum, resources, or assignment sections), and additional information about the action.

Following this, descriptive statistics were employed to analyse and interpret the data. Additionally, correlation analysis was conducted among the main components of the dataset to identify which variables most significantly impact student performance.

# 4 COURSE DESCRIPTION AND PARTICIPANTS

The course "Business Informatics" is a first-semester bachelor course of the specialist study program "Information Technology in Business Applications" offered at the University of Zagreb, Faculty of Organization and Informatics in Varaždin, Croatia. The course syllabus covers several key topics, including an introduction to information systems and their applications in business, a detailed exploration of computer hardware and software (the fundamental components of information systems), and foundational principles of information system security.

Delivered as a blended course, all teaching materials and methods have been designed for such delivery within Moodle. The topics covered in lectures are supplemented with various online resources, such as videos and quizzes integrated into the Moodle. The course content is organized into a sequence of lessons, prepared as asynchronous materials for the online component, serving as both a primary source of information and a mean of reviewing topics discussed in onsite and in online lectures.

The structure of the course includes seven knowledge domains, as shown in Figure 1, while each knowledge domain consists of several lessons.

Each lesson ends with a short test, which students must solve successfully to progress to the next lesson (a part of conditional activities). Achieving the required result in all lessons within a knowledge domain is a prerequisite to access the final self-assessment quiz at the end of each knowledge domain. Such a learning path was implemented as a completion tracking and conditional activities feature in Moodle. It enables teachers to specify when a certain activity shall be hidden or enabled for students according to the planned course design.

Since the students took the self-assessments outside the class as an optional activity, those results are not included in their final grade. They are designed as a student self-monitoring activity opposite to the formal online midterm exams which are obligatory and conducted within the Moodle course. A total of two midterms are performed: the first in the middle of the semester (Week 8) including knowledge domains 1 and 2 and the second in the final week (Week 16) including all knowledge domains.

Besides the formal tests and self-assessments, students are also given short flash-tests during lectures, as warm-up activities covering the content from the previous domain knowledge. In total, 4-5 flash-tests are provided during the semester. Students' final grades are created based on their results from flash tests, 1st midterm and the 2nd midterm exam.

During the 2023/2024 academic year, a total of 117 students were enrolled in the course. At the end of the 16th week a total of 99 students (84.6%) finished the course out of which 31 were female students (31.3%) and 68 male students (68.7%).

To analyse students' performance and identify areas where they may be struggling during the course, as well as to implement targeted interventions with the goal of improving student outcomes, the student activity logs and their scores were exported and processed.

# 5 RESULTS

The dataset used in this paper was collected during the first semester of academic year 2023/2024. Since the course was delivered in blended mode, students were required to complete part of the activities (e.g., view, add, update…) off campus - through LMS (e.g., forum posts, self-assessments, lessons completed…). Since the LMS automatically stored a lot of activity logs during the course about every student enrolled, they were exported as a datasheet after the course had ended. More than 330000 activity logs were exported

| **Course week** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **11** | **12** | **13** | **14** | **15** | **16** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Knowledge domain** | Information Systems | | | | Information Systems Security | | Basic Computers Principles | | **1st Midterm Exam** | Central Unit of a Computer | | Memory Unit | | Input/Output Unit | Computer Software | **2nd Midterm Exam** |

Figure 1: Organization of the course across knowledge domains and weeks.

for all students enrolled. After the data wash, a total of 277899 activity logs were prepared for further analysis within a pivot table including the columns “Student ID”, “Date and time”, “LMS Module (Lesson, Forum, Test…)”, “Final Grade Course”, “Week of the Course” and “Class attendance” that were analysed.

Furthermore, to analyse the relationship between monitored activities/objectives, data on the results for each individual student (based on “Student ID”) were exported to the new datasheet and later processed in SPSS Statistics (version 29.0.0.0). The monitored activities/objectives included: “1st Midterm Exam”, “2nd Midterm Exam”, “Flash tests”, “Self-assessment quiz”, “Class attendance”, “Number of logs” and “Final grade”.

The analysis was started by reviewing the distribution of logs per week which include access to lessons, self-assessment attempts, flash tests and forum views (see Figure 2).

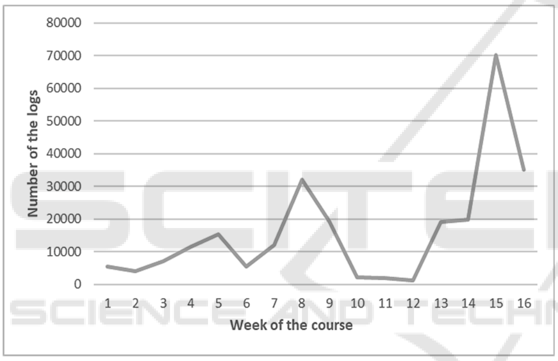


Figure 2: Distribution of logs per week.

It can be noted that the peaks in the graph occur in four stages of the course: the 5th, 8th, 13th, and 15th week, when course activity is particularly intensive. The increases in activities during the 5th and 13th weeks are linked to the assessments of practical assignments. Notably, student activities rise steadily until the 5th week, when their knowledge from the practical assignments is assessed, before dropping sharply in the 6th week.

Additionally, there is a noticeable increase in student preparation between the 7th and 8th week, coinciding with the schedule of the midterm exam. In the 13th week, students face a second assessment for the practical assignments, but this time, there is no significant drop in activity. In fact, student engagement is higher during these second practical assignments compared to the first. A significant increase in student activity is also noted in the 13th week, as students prepare for the second midterm exam and complete any remaining course tasks.

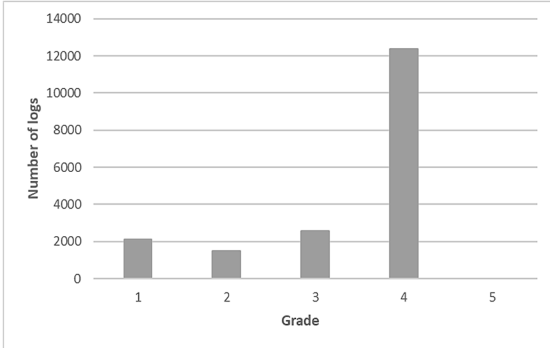


Figure 3: Frequency of logs by grade.

Regarding online activity and final grades, Figure 3 which indicates overall number of logs per grade, reveals that students with the highest grades were also the most active in the LMS, recording over 12,000 logs - significantly more than students with lower grades In Croatia, the grading system ranges from 1 (lowest/fail) to 5 (highest/excellent), but there were no students in the analysed semester achieving the highest grade within LMS (chart displays grades 1 and 4, with the size of the populations 29 (1)-42 (2)–24 (3)–5 (4). It is important to note that in this blended course, the activity levels of students with lower grades (1-3) do not differ significantly. This suggests that, based on their access to resources, it is not possible to predict their final results, except for the most active ones. Students who did not meet the requirements for a grade continuously throughout the semester were not taken into account.

However, a different conclusion can be made if we take a closer look at the distribution of activities related to self-assessment quizzes for each course week presented in Figure 4. Over the 16-week period, the activity levels of all students are generally low for the most weeks, with increased activity around weeks 8 and 15 when midterms are taking place. It is evident that students with lowest grades exhibited minimal activity in the early weeks, with a slight increase in week 8 and in week 15, reaching an average of 3.5 self-assessment tests completed per student (out of 7). Students with grade 2 demonstrated somewhat better activity, particularly around week 8, and significantly increased their self-assessment completion by week 15, similar to students with a grade of 3 (averaging 6 out of 7).

Interestingly, students with grade 3 had similar activity levels to those with grade 4 around week 8, indicating that they have completed both self-assessment quizzes covering the material for the first midterm exam. However, the most notable difference among the grades appears in week 15, when grade 4

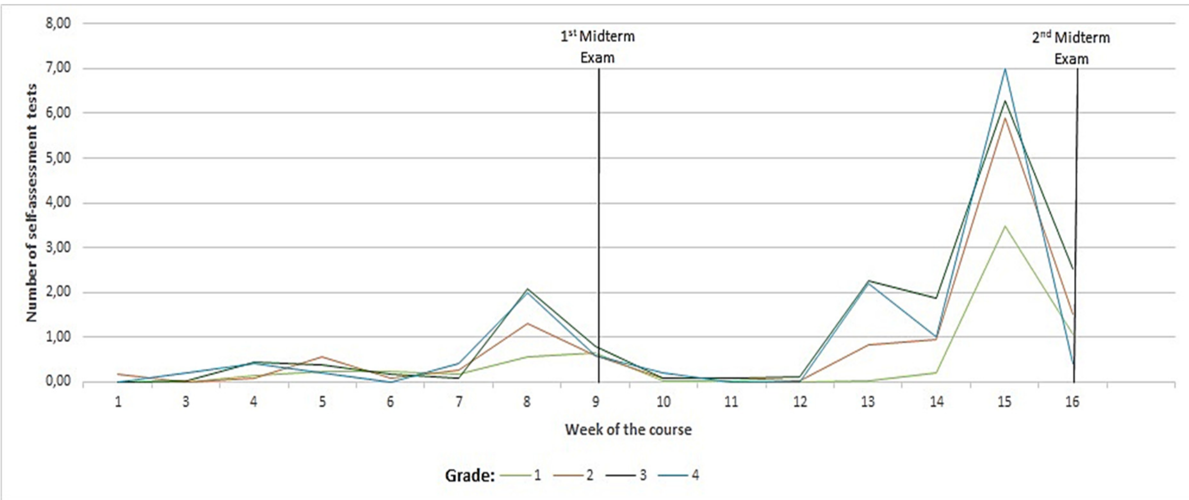


Figure 4: Self-assessment test activity based on student grades.

students completed all 7 self-assessments, while grade 3 students averaged around 6, suggesting that most grade 3 students did not complete all of the self-assessments.

During the course, a total of 7 self-assessment quizzes were available as shown in Figure 5. As mentioned earlier, the first midterm exam included domains 1 and 2, "Information systems" and "Information Systems Security" respectively. Students have started completing the first self-assessment quiz in the 3rd week, with the highest number of attempts in the 8th week, during the preparation for the midterm exam.

It can also be observed that students continued working on the first two self-assessments until the end of the semester, particularly as preparation for the second midterm exam, basically since the second midterm exam included some questions from the first two knowledge domains. Although the first of the remaining self-assessments was available from the 7th week, it can be noted that students learned "periodically", having activity peaks only around midterm periods. This is also supported by the fact that students started accessing self-assessments in the 13th week as a way of preparation for the second midterm.

Finally, the last part of analysis refers to reviewing the correlations between the monitored activities/objects. The correlation matrix in Table 1 shows several significant relationships between various factors that contribute to monitoring student performance.

Since the Final grade is calculated as the sum of the points earned on the 1st and 2nd Midterm exams, Flash tests, and the Self-assessment quiz, a strong

Table 1: Correlation matrix between factors that contribute to monitor student success.

| **Correlations** | | | | | | | |
|---|---|---|---|---|---|---|---|
| | **1ME** | **2ME** | **FT** | **SAQ** | **CA** | **NL** | **FG** |
| **1ME** | 1 | 0,396[1] | 0,274[1] | 0,275[1] | -0,063 | 0,366[1] | 0,709[1] |
| **2ME** | 0,396[1] | 1 | 0,283[1] | 0,040 | -0,040 | 0,128 | 0,773[1] |
| **FT** | 0,274[1] | 0,283[1] | 1 | 0,160 | -0,068 | 0,211[2] | 0,311[1] |
| **SAQ** | 0,275[1] | 0,040 | 0,160 | 1 | -0,068 | 0,595[1] | 0,241[2] |
| **CA** | -0,063 | -0,040 | -0,068 | -0,068 | 1 | 0,042 | -0,021 |
| **NL** | 0,366[1] | 0,128 | 0,211[2] | 0,595[1] | 0,042 | 1 | 0,352[1] |
| **FG** | 0,709[1] | 0,773[1] | 0,311[1] | 0,241[2] | 0,021 | 0,352[2] | 1 |

*[1]Correlation is significant at the 0.01 level, [2]Correlation is significant at the 0.05 level*

*Explanation: 1st Midterm exam (1ME), 2nd Midterm exam (2ME), Flash tests (FT), Self-assessment quiz (SAQ), Class attendance (CA), Number of logs (NL), Final grade (FG)*

positive correlation between the 2nd midterm exam and the final grade (r = 0,773, p=0,01), predicting that the performance on the 2nd midterm exam is the key predictor in achieving success in the course. Also, the midterm exams show strong positive correlation with final grade, which indicates the importance of the 2 major assessments as a key component in achieving overall success in the course. Moderate positive correlation was found between flash tests and the

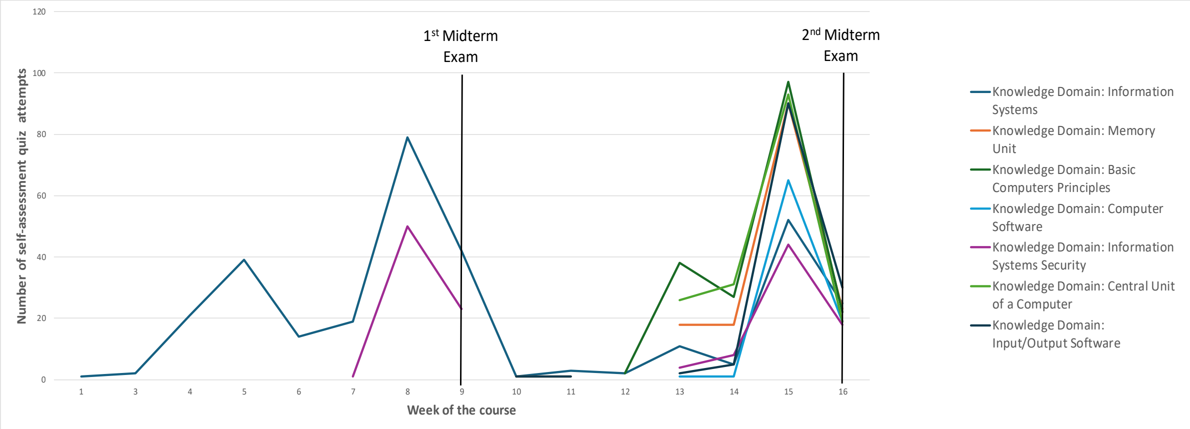


Figure 5: Self-assessment quiz attempts per week of the course.

final grade (r=0,311, p=0,01) which indicates that active student engagement (flash tests were solved during lessons) have a moderate impact in achieving positive final grade. Also, the number of logs which indicates an overall number of logs per student, and final grade have a moderate positive correlation (r=0,352, p=0,01). Although the self-assessment quiz demonstrated a strong correlation with the number of logs (r = 0,595, p = 0,01), correlation to the final grade was weaker (r = 0,241, p = 0,05). This suggests that although the self-assessment activities may encourage higher levels of engagement, they do not necessarily lead to improved final grades directly.

# 6 DISCUSSION

Re RQ1 discussing in what way can student logs be used to analyse students' performance it is evident that in a blended environment, where students alternate between face-to-face and online teaching and learning, LMS logs can help teachers to identify how well students are balancing both delivery modes. These logs capture activities like lesson access, quiz attempts, participation in forums, and interactions with learning materials, providing a comprehensive view of students' online learning behaviour. However, some additional tracking elements are needed to capture their face-to-face activity, as in this case we used class attendance and flash-tests written during face-to-face lectures. Besides these information, the teacher gets clear insight about the student time management (when do students usually approach specific resources) and after the 1st midterm they are able to identify potentially at-risk students. They are also able to note which parts of the course content are visited more frequently than others, and which ones might not be visited at all, leading them to revise those materials or the course requirements.

The analysis of LMS logs allows teachers to track student progress and intervene early to support students in need. In the case of a blended course, it is important to note that the number of logs may not reflect real student engagement and knowledge. The data in this example showed a very slight difference in the number of logs between students with final grades 1 to 3. However, the self-assessment activity is notably different for students with different final scores/grades, which is fully in line with study from Schön (2022) who has also shown that completion rates of online quizzes can predict final exam performance.

Re RQ2 aimed at identifying the variables that most influence the students' performance using course-agnostic LMS log data, the correlation matrix in the results reveals that midterm exam performance and the number of logs are significant predictors of final grades, highlighting research that demonstrates the predictive power of LMS data in early identification of students at risk of underperformance (Gašević et al., 2016; Tamada et al., 2022).

Based on the analysis of correlations, several variables have been identified as influential on student performance:

1. **Number of Logs:** The overall number of interactions in the LMS has been shown to correlate with higher grades. This is also supported by Kadoić & Oreški (2018) who found a positive relationship between the number of Moodle log entries and final grades, indicating that students who frequently engage with course content tend to perform better. Such finding is also supported by other studies (e.g. Conijn et al., 2017; Baginda et al. 2022) where LMS log frequency was shown to be a common indicator of performance.

**2. Engagement in Self-Assessment Quizzes:** In the given study, students with higher grades consistently completed more self-assessment quizzes, especially around midterm periods. Although self-assessment quizzes were highly correlated with overall activity (r = 0,595), they had a lower direct correlation with final grades, suggesting that while they might boost engagement, they may only indirectly influence performance.

**3. Participation in Flash Tests:** Flash tests, as mandatory, but brief in-course assessments, have a positive relationship with final grades (r = 0,311), highlighting the impact of frequent, low-stakes testing on learning outcomes. Rotelli, Fiorentino & Monreale (2021) suggested that these micro-assessment engagements are valuable for reinforcing material and maintaining consistent engagement, which contributes to better academic outcomes.

**4. Midterm scores:** The scores from structured assessments showed the strongest correlation with final grades, especially the 2nd midterm (r = 0,773). This aligns with Gašević et al. (2016), who found that scores on significant assessments derived from LMS logs are critical predictors of final performance. This variable acts as a summative reflection of students' knowledge and learning throughout the course, meaning that based on the 1st midterm the teachers could detect failing students.

**5. Course Material Access and Forum Participation:** This research has found a moderate correlation between access to materials and forums and the final grade. That might be related to the fact that some students had printed materials and were not assessing LMS. A positive relationship between access to materials and final grade was also supported by Baginda et al. (2022) who identified that accessing core LMS features, such as course materials, assignments, and forums, was strongly associated with higher grades. Regular interaction with these resources suggests proactive learning and engagement with course content. This is consistent with the findings of Li et al. (2018), who emphasized that students who frequently interact with learning resources and engage in forums demonstrate higher levels of comprehension and academic performance.

The last interesting finding in respect to RQ2 in this research revealed that course participation does not affect student performance, which is probably related to the fact that students were required to attend at least 65% of face to face lectures.

Re RQ3 aimed at identifying areas where teachers can use LMS logs to enable better student performance this research highlights that students with higher activity levels, such as frequent self-assessment attempts and access to resources, generally achieved better grades. By monitoring these logs, teachers can detect early signs of underperformance, such as a lack of engagement before assessments, and intervene accordingly. This is supported by research from Gašević et al. (2016) and Tamada et al. (2022), which emphasize the use of LMS data for predicting at-risk students. Predictive models based on these logs can enable teachers to offer timely support, such as additional resources or feedback, improving students' chances of success. As seen, more interactive materials (self-assessments, flash-tests…) could provide students with more opportunities to self-test and perform better and teachers with more data for analytics and prompt reaction and course redesign.

Within the context of this course, where around 30% of students fail the course during the continuous monitoring, the conclusions provide teachers with the clear guidelines on how to redesign and when to react and provide students with more stimuli to successfully conclude the course. Further analysis of the student feedback on course delivery, content and available (self-)assessment options will enable deeper analysis and improvements of the course.

# 7 CONCLUSION

This study, conducted in an institution with limited resources, sought to identify patterns in student engagement and performance using LMS log data. The results demonstrate the viability of using accessible and affordable methods for monitoring student progress in a blended learning environment. Key findings show that the majority of student activity is concentrated around major assessments, as well as support the fact that the students who engage more consistently within LMS are also generally performing better. However, while self-assessment activities correlated with higher levels of engagement, they did not strongly predict final grades.

Importantly, this study confirms the potential for institutions to leverage existing data to provide timely feedback for students at risk of underperforming, allowing for interventions such as adjusted teaching methods or additional assignments tailored to both advanced and struggling students. These findings can help teachers make predictions for upcoming semesters, offering live recognition of both at-risk and high-achieving students. Since this was one of the first courses where students interacted with LMS since entering higher education, the implications of this research can be beneficial to other teachers, potentially yielding long-term positive effects for students across the study programme.

To further support educators in applying these findings, we recommend the integration of automated alerts within the LMS platforms to identify and notify students at risk based on engagement metrics.

Future research could explore student perspectives by incorporating surveys, complementing the log data with qualitative insights into student experiences and engagement. Analysing students' perceptions of course components, perceived workload, and their reasons for engagement patterns could provide insights to refine predictive models and develop more effective teaching interventions.

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