Making the Most of Slides and Lecture Captures for Better Performance: A Learning Analytics Case Study in Higher Education

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Abstract

The provision of educational material in higher education takes place through learning management systems (LMS) and other learning platforms. However, little is known yet about how and when the students access the educational materials provided to perform better. In this paper, we aim to answer the research question: 'How do the high achievers use the educational material provided to get better grades?'. To answer this question, the data from two educational platforms were merged: a LMS, and a lecture capture platform. We based our analysis on a series of quizzes to understand the differences between high and non high achievers regarding the use of lecture recordings and slides at different moments: (1) before and (2) while solving the quizzes, and (3) after their submission. Our analysis shows significant differences between both groups and highlights the value of considering all the educational platforms instead of limiting the analyses to a single data source.

Keywords: learning management system, lecture captures, educational material, learning analytics, higher education

1. Introduction

Educational material, e.g., slides and lecture captures, has been widely used in educational settings to support teaching and learning practices. They have several benefits for both teachers and students, and over the past two years, they have been cornerstone elements driving and supporting distance learning modalities during the pandemic. With the increase in the number of learning platforms used for delivering educational content by providing learning material to the students, higher education institutions might face difficulties to identify which learning platforms the students find more engaging or supportive for their learning processes compared to those less beneficial (López Flores, Óskarsdóttir, et al., 2022; Nworie, 2021). Furthermore, little is known to date about how students use the learning materials provided to support their own learning process while studying and solving assignments.

This paper focuses on analysing undergraduate students' activity related to the use of educational material to understand how the students use it to support themselves and perform better. In particular, we are interested in knowing the differences between 'high achievers' and 'non high achievers' regarding the use they make of slides and lecture captures. Through our analysis of the students' activity, we aim to answer the following research question: *How do the high achievers use the educational material provided to get better grades?* To that end, the analysis focuses on one undergraduate course taught in Spring 2022 to 59 students, and their interactions with the educational material related to solving a series of nine class content related quizzes. Two data sources that provide insightful information about undergraduate students' learning behaviour are combined and analysed for the purpose of this paper; the learning management system where the students had access to the slides, and a lecture capture platform where they could access both the lecture recordings and the slides. We perform a two sided analysis, studying lecture capture activity and slides activity.

Our findings show that high achievers tended to make better use of both learning platforms as the course progressed. In contrast, non high achievers showed lower engagement levels, especially with the lecture

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capture platform.

The rest of this paper is organised as follows. In the next section, we discuss related work on Learning Analytics self-regulation research. In Section 3 we present the methodology used in this research, followed by the results in Section 4. The paper concludes with a discussion on the implications and limitations of our work and directions for future work.

2. Related work

2.1. Learning analytics and students' self-regulation

The education provision in higher education institutions relies on several educational platforms, such as Learning Management Systems (LMSs), e.g. Canvas, Moodle, or Blackboard; and other interconnected external learning platforms, e.g. discussion forums, lecture recordings, coding platforms, etc. (Islind et al., 2021; López Flores, Óskarsdóttir, et al., 2022). Those platforms not only facilitate the students' access to the learning material, they also provide flexibility for the students to learn at more convenient times by providing on-demand access to those materials, meaning the students' physical attendance to the lecture rooms is no longer needed (López Flores et al., 2021). Furthermore, since the pandemic started, the education provision was significantly modified to meet the students' and teachers' needs, and traditional teaching methods were adapted to meet new distance, blended and hybrid modalities (Code et al., 2020).

The aforementioned platforms capture and store the students' detailed activity within the platform elements and modules; as well as the students' interactions with the learning materials provided by the instructors. In consequence, large data sets of time stamped click-streams -or digital traces- are produced, providing insights into educational practice (Gašević et al., 2015). The massive amounts of educational data and digital traces from LMSs and interactive learning environments are a common source of data in learning analytics research and have been widely used with the objective of investigating several elements of learning and teaching processes (Nguyen et al., 2020; Tsai et al., 2020). Previous research based on these data has highlighted learning platforms' data are a helpful resource that allows to investigate the students' engagement, self-regulation, and time management skills (Jovanović et al., 2021; Motz et al., 2019; Sher et al., 2020).

Self-regulated learning has been defined as a process that involves four recursive stages: (i) task definition, (ii) goal setting and planning, (iii) enacting study tactics and strategies, and (iv) adaptation (Winne and Hadwin, 1998). This model of self-regulated learning defined by Winne and Hadwin (1998) has been extensively adopted in computer supported learning environments (Panadero et al., 2016). In this model, given a learning task; (i) and (ii), involve the students' task understanding, and their plan for addressing it, respectively. For the purposes of this paper, this case study focuses on (iii) and (iv). In (iii), the study tactics and strategies selected based on (i) and created in (ii) are implemented, whereas in (iv) the students change their learning strategies based on the experience and evaluation elements. Several indicators based on learning platforms click-stream have been created to analyse self-regulation behaviours, to build dashboards, and inform both learners and instructors (Matcha et al., 2019). Some examples of those indicators are the students' level of engagement, time utilisation, posting activity, etc. In the following subsections, we present related work on self-regulation and learning strategies based on data gathered from LMSs and lecture captures, the indicators created, and the main results obtained from the analysis of those indicators.

2.2. Leaning Management Systems' click-stream data

Previous research has confirmed that activity indices from LMSs' web logs provide a reliable representation of learner behaviour (Quick et al., 2020) and student engagement (Motz et al., 2019) in varied learning environments. Joksimović et al. (2015) used trace data to examine the effect that the number and duration of four interaction types had on the students' final grades. Their results indicate a positive correlation between grades and the interactions of the student with the learning platforms provided. Sher et al. (2020) used LMSs click-stream data to study consistency patterns in blended courses by identifying five student clusters based on the students' grades, consistency in discussion forum activities, and consistency in assignments activities. Their research highlights the need for investigating the consistency of study patterns over time. Similarly, Jovanović et al. (2021) included logs from the LMS in discussion forums, the main course page, grades and learning materials views to study the association between academic achievement and the students' engagement with the learning activities. In their studies, the time spent online, consistent contributions to discussion forums, and regular access to the learning material were significant predictors of high academic achievement.

Recently, researchers have focused on analysing how and when the students interact with the LMSs and its content, as well as the relationship between the interactions' time and the students' academic performance. Sher et al. (2022) investigated the differences on when the students interacted with the LMS using three different types of electronic devices. Their research shows the students generally use two or more types of devices to access the course content, and significant variations were found on the time they prefer to use each of them. Saqr et al. (2018) and Saqr et al. (2019) focused on analysing the temporality of student engagement actions. They based on LMS time stamped data to study the differences in engagement patterns between high and non high achievers at different moments during the day, week, course, and year. Their research shows that despite both high and non high achievers tend to decrease their activity levels as the course progressed, their interaction patterns were significant predictors of academic achievement. Accordingly, the authors highlight the importance of further investigating time as an indicator of how the students self regulate their learning. In this paper, we contribute to that call.

2.3. Lecture Capture viewing data

Lecture captures have several benefits for students and teachers, their provision promotes independent study, attendance flexibility, and time management skills acquisition (López Flores et al., 2021). The data provided by such lecture capture platforms have been extensively investigated, providing important insights into teaching and learning practices. For example, Rodriguez et al. (2021) focused on identifying self-regulated learning patterns based on indicators of video completion and time management. In their research, the click-stream data were used to count the students' clicks on the pre-recorded videos provided by the teacher, classified based on their time-stamps, and used to identify four types of self-regulated behaviours. Edwards and Clinton (2019) analysed how the students used the lecture recordings. They found the students used the lecture captures as a substitute for attending live lectures. This constitutes one of the main instructors' concerns regarding the use of lecture capture platforms to complement the learning environment because such a choice has implications on the students' levels of attendance to live lectures and verbal engagement (O'Callaghan et al., 2017). Nonetheless, it has been found that the preference for utilising lecture recording platforms against attendance to live lectures is correlated with the students' learning profiles and as well as their previous experience using the particular learning platform (López Flores, Islind, et al., 2022). Consequently, there is a growing need of examining lecture capture platforms in general and the use of lecture recordings in particular in varied educational settings to gain a better understanding of the way the students learn and benefit from their use (O'Callaghan et al., 2017).

3. Methods

3.1. Data sources

This study encompasses data from two data sources: (1) a learning management system (LMS), and a (2) lecture capture platform. The data from Canvas, which is the LMS, were accessed through several reports from the LMS itself and its connected Application Programming Interface (API).

Regarding the lecture capture platform, the data were gathered from Echo360 ("Echo 360", 2021). The lecture capture platform is available to all teachers at the university to create and deliver educational material and likewise, all students, are also enabled access to it. Similarly to the LMS reports, the data were gathered from the Echo360 API. The reports included from these data sources are described in Table 1. All students enrolled in the course were active in both learning platforms.

3.2. Course structure

The course selected was Data Analysis; it is an elective course offered to second and third year students enrolled in any undergraduate program within the Department of Computer Science. In the term Spring 2022 the course had 59 students enrolled. The minimum grade to pass undergraduate courses at Reykjavik University is 50 out of 100 points. The course's assessment comprised five coding assignments (20%), the mid-term exam (20%), nine quizzes (20%) and the final project submission and presentation (40%). The only element in the assessment structure that was meant to be fulfilled in groups was the final project. The five coding assignments were handed in and graded in an external learning platform for coding collaboration, and the interactions within that learning platform are not analysed as a part of this paper. Regarding the quizzes, they were embedded into the LMS with a fixed unlocking time for all students and that data therefore outlines an important element in our analysis. The quizzes were automatically graded through the LMS, and only the highest seven scores were counted for the final grade.

The course was taught for 11 weeks with two

Platform	Report	Description
LMS (Canvas)	Students	List of enrolled students' names, user ID's, and login ID's.
	Modules Items	List of all elements in the modules section, title, content IDs, and URLs.
	Assignments	List of all course assignments (Title and ID's), deadline, and points.
	Assignments submissions	Detail of student submissions, submission time, and score.
	Quizzes	List of all course quizzes (Title and IDs), question count, and points.
	Quizzes submissions	Detail of student submissions, start time, finish time, and time spent.
	Page views	Detail of pages' views in all components in the LMS, user IDs, and URLs.
	Grades	List of enrolled students' login IDs, and final course grade.
Lecture capture platform (Echo360)	Section	Course ID, Course Name, Instructors login IDs, and LMS course ID.
	Lessons	List of all course lessons, names, time, and live stream indicator.
	Video views	Weekly report of video watching activity: login ID, timestamp, video Id, video name, and duration.
	Presentations	List of presentation events, IDs, timestamp, and student login ID.

Table 1. Reports from the LMS (Canvas) and the lecture capture platform (Echo360) API included.

lectures and one practical session per week. During the first five weeks, the course lectures were pre-recorded by the teacher and uploaded to the lecture capture platform Echo360 in advance. This was done because of restrictions due to the covid-19 pandemic. In addition to the recordings, the teacher established drop-in sessions to solve questions related to the lecture recordings. During these five weeks, 16 recordings were provided to the students, allowing them to get used to the lecture capture platform and its features. For the remaining six weeks, the lectures were on-site at the university premises, but live-streamed through Echo360, recorded and uploaded afterwards into the lecture capture platform. This structure provided the students with the flexibility to choose whether they would prefer to attend the lectures in person, to watch them live, or to watch the recording at a more convenient time for them. During these latter six weeks, a total of ten lecture captures were uploaded to Echo360. Similarly to the lecture captures, the slide decks for each lecture were provided by the teacher in both platforms, Canvas and Echo360. Additionally, for each of the first nine live-streamed lectures, the students had to solve one of the quizzes. The quizzes unlocked automatically once the lecture started and their deadlines were fixed at midnight on the same day. However, late submissions were allowed and the students could take as much time as they needed to solve them and submit their final answers without a grade penalty. Despite that, most of the students solved their quizzes "on time". However, as it could be expected given that only the highest seven grades were taken into account towards their final grade, the last two quizzes were those with the highest number of students with "missing" submissions (See Figure 1).

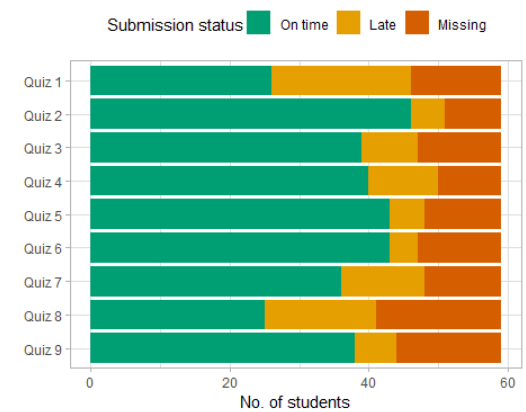


Figure 1. Distribution of "on time", "late" and "missing" submissions for the 59 students enrolled.

3.3. Analysis

The aim of this study was to understand how the students used the slides and lecture recordings to perform better. Accordingly, we decided to focus on analysing the students' activity related to solving the nine quizzes and its relationship with the final grade obtained in the course. The level of significance for all statistical tests computed was set at 0.05. The correlation coefficient between the quizzes and the final grade is $\tau = 0.669$ (See Figure 2), indicating the quizzes are a significant component of the final grade. Moreover, the students were classified into high achiever and non high achiever based on their final grade. The students with a final grade of at least 80 were classified as high achievers (33 out of 59 students), and as non high achievers otherwise. Only three students got less than 50 points and failed the course.

The reports described in Table 1 were combined

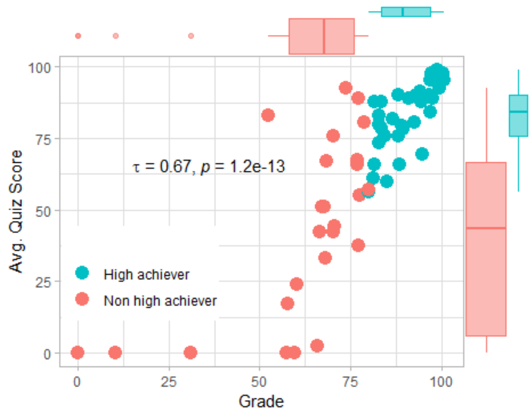


Figure 2. Correlation between the average score in the quizzes and the final grade in the course.

based on the students' login ID, quiz names, video ID, video name, presentation ID, and presentation name. As the LMS provided exact information about the starting and ending times of quizzes' solving, the students' activity with the educational materials corresponding to each quiz was divided into activity *before* starting the quiz, *during* the solving time, and *after* submitting the quiz. Table 2 displays the mean and median values for the final grade, the total points got in the quizzes (out of 41), and the average time spent solving the quizzes.

Variable	High achiever		Non high achiever	
	mean	median	mean	median
Final Grade	90.4	89.4	60	67.9
Quiz Score	33.9	34.5	17	17.8
Solving time (hours)	4.1	0.3	0.4	0.1

Table 2. Mean and median values split by high achievers and non high achievers.

4. Results

Taking into consideration the sample sizes and variance, Mann-Whitney U-tests and t-tests were used to evaluate for differences in the variables' distribution (Newbold, 2013) between high achiever and non high achiever students. Statistically significant differences between both groups were found for grade, quizzes score and solving time. Table 3 shows the statistics and p-values obtained from the statistical tests. As expected, the students classified as high achiever got higher grades at the end of the course and their scores in the quizzes were also higher than non high achiever students. Moreover, the tests also indicate the high achiever students spent more time solving the quizzes compared to the non high achiever students.

Variable	Statistic	p-value
Final Grade	t=8.8921	2.667e-10
Quiz Score	w = 99.5	4.961e-07
Solving time (hours)	w = 209	0.0007995

Table 3. Statistics and p-values for differences in the distribution of high achievers and non high achievers.

4.1. Lecture capture activity

The students' watching activity within the lecture capture platform was gathered using the Video views report from Echo360 as described above (Table 1). In this report, each entry corresponded to 30 seconds of video watched. Therefore, by aggregating the information provided by the report is possible to compute the minutes watched for each lecture capture. Despite small variations in the lectures' length, the ratio of video watched was computed to allow comparisons between groups and weeks. To identify the differences in the lecture capture usage between high achievers and non high achievers, the watching activity that took place before, during, and after the quizzes' were submitted, was compared in two different ways: (1) Analysing the activity of all quizzes together, and (2) splitting the watching activity by quiz, to look for changes in the usage of the lecture captures as the course progressed.

Results from the Mann-Whitney U-tests displayed in Table 4 show there are significant differences between the ratio of video watched before, during and after the quiz submission for the high achievers compared to the non high achievers. Median and mean values for the ratio of video watched in Table 5 indicate that on average, the high achiever students watched the lecture captures more than the non high achievers.

Variable	Statistic	p-value
Ratio before	W = 278.5	0.0117
Ratio during	W = 308	0.04478
Ration after	W = 304	0.03261

Table 4. Statistics and p-values for differences in the distribution of lecture capture ratio watched.

Variable	High achiever		Non high achiever	
	mean	median	mean	median
Ratio before	0.08	0.01	0.04	0.0
Ratio during	0.16	0.01	0.03	0.0
Ration after	0.07	0.0	0.02	0.0

Table 5. Mean and median values for lecture capture ratio watched.

Considering the lectures corresponding to the quizzes content were delivered live and the students were allowed the option to attend in person to them; accessing the lecture capture platform was not strictly needed in order to access the class content or solve the quizzes. For that reason, in addition to the previous plots and tests presented, the following section includes merely the students with watching activity to investigate the differences in their watching patterns and the relationship with their academic performance through the proxy of their grade. Figure 3 shows the distribution of ratio watched before, during, and after the quiz submission respectively. It is noticeable that non high achievers watching behaviour differs from the watching behaviour of high achievers.

Similar to the submission patterns identified before, the students' watching behaviour for the last quizzes was distinct from their watching behaviour for the first quiz submissions. For lecture captures watched before (during) non high achievers solved the quizzes, the ratio of videos watched dropped considerably after the first seven (six) quizzes. Regarding lecture captures watched after the quiz submission times, most of the students that were actively utilising and checking out the recordings were high achievers.

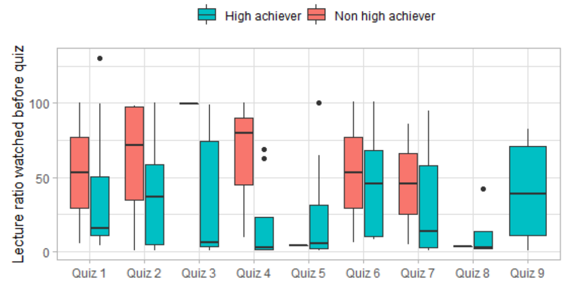
In contrast to non high achievers whose activity dropped for the last quizzes, the high achievers' watching activity before, during, and after was more consistent along the course. However, Figures 3(b) and 3(c) show the high achievers watching activity, despite being more consistent, was not necessarily constant through the course as the ratio of lecture capture watched while solving the last quizzes was higher than the ratio watched during the first quizzes. Contrarily, the ratio watched after the quiz submissions seems to decline as the term progressed. In order to evaluate such changes in the watching behaviour, chi-squared tests for trends in the proportions were computed. The tests statistics were calculated using the median minutes watched out of the total minutes of each lecture capture. The tests results were significant for the ratio during and after the quiz submission (See Table 6).

	χ^2	p-value
Before	3.143	0.07622
During	24.752	6.521e-07
After	28.467	9.53e-08

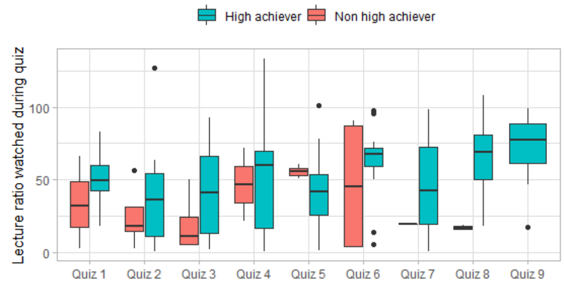
Table 6. Test results for trends in the lecture ratio watched by high achievers.

4.2. Slides activity

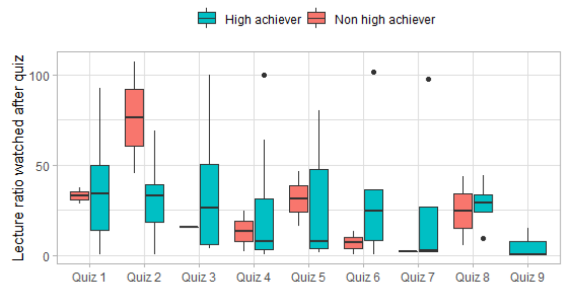
As described in Section 3.2, the teacher uploaded the slides related to each lecture to both learning platforms,



(a) Watched before



(b) Watched during



(c) Watched after

Figure 3. Distribution of the lecture ratio watched before (a), during (b), and after(c) each quiz.

Canvas and Echo360. As the students could access the slides on any of the learning platforms, both were included in the analysis. However, the structure of the activity reports provided by the platforms and the information contained on them were different. The report *Presentations* from the Echo360 API provided information regarding the students' engagement with the presentations uploaded by the teacher through the platform. In this report, each row represents one viewing event (one slide or whole slide deck view) of the presentations. In contrast, in the report *Page Views* from the Canvas API, each row represents one of the URLs the student accessed through the LMS. Related to the slides, the data do not only include information on the number of viewing events (whole slide deck) that the students had through the system, but also information related to the number of slide deck downloads.

The slides were widely used by the students throughout the course, 81% of them accessed the slide decks at least once through any of the learning platforms. However, the percentage of high achievers (90%) accessing the slides was significantly higher than the percentage of non high achievers (69%) (χ^2 = 3.18, p-value = 0.03705). To address to what extent the access to the slides changed between groups as the course progressed, the slides activity was split by the quiz the slides belonged to. Figure 4 displays the percentage of high and non high achiever students accessing the slide decks for each quiz. Similarly to the watching behaviour addressed above, the percentage of non high achievers accessing the slides of Quizzes 8 and 9 was lower than the percentage for the previous quizzes. In contrast, the percentage of high achievers accessing the slides was much more consistent across quizzes. On average, 75% and 41% of high and non high achievers accessed them respectively. The percentage differences are significant for eight of the nine quizzes. Quiz 3 was the only one without significant differences between groups (Prop-high = 67%, Prop-non = 50%, χ^2 = 1.0546, p-value = 0.1522). Furthermore, Figure 4 also displays which learning platform the students used to access the slides. It is noticeable that most of the students in both groups accessed the slides either through both platforms or Canvas exclusively; whereas a limited number of students accessed the slides only through Echo360.

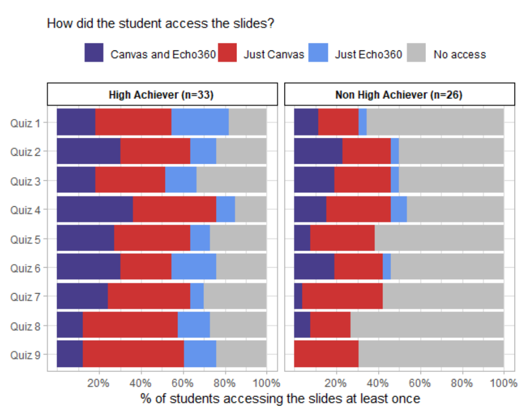


Figure 4. Percentage of students accessing the slides. Split by quiz and platform.

To address the differences in the time the students in each group accessed the slides, the activity was split using the start and end timestamps of each quiz submission. Statistical tests were performed for differences in the proportions before, during and after. Results are showed in Table 7. Compared to non high achievers, a higher percentage of high achievers accessed the slides before starting the quiz, while solving the quiz, and after their quiz submissions.

Time	High achiever	Non high achiever	χ^2, p-value
Before	73%	42%	4.38, 0.01
During	90%	54%	8.67, 0.001
After	79%	54%	3.08, 0.039

Table 7. Proportion test results for differences in the percentage of students accessing the slides.

Regarding the slide deck downloads, the difference in the proportion of high and non high achiever students downloading the slides to their personal computers was smaller than the difference in accessing them through the platforms. For high achievers, about 35% of them downloaded the slides at least once during the term, whereas for non high achievers the proportion was 28%. The proportion of students downloading the material for each quiz is displayed in Figure 5. Contrary to the differences between groups accessing the slides, for downloading the material no difference was found in the number of downloads before, during or after the quizzes' submission times. Nevertheless, most of the downloads for both groups took place while the quizzes were being solved, indicating those students also used the slides to support themselves and perform better.

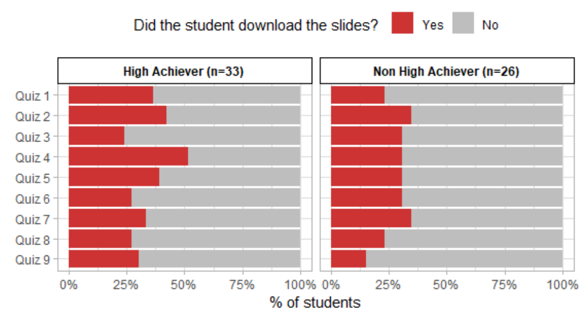


Figure 5. Percentage of students downloading each the slide deck at least once during the course.

5. Discussion and Conclusion

This research delves into students' use of lecture captures and slides to get better grades. As presented in Section 2, several indicators based on the students' activity in learning platforms have been created to study the students' self-regulation behaviour. In this paper, considering the course's structure and assessment elements, the activity proceeding from solving a series of nine quizzes was used to analyse the usage of the learning materials. We address both the use of learning materials and how the students change their use over time, by analysing indicators created based on the students' time spent watching the videos corresponding to each quiz, their access to the slides provided, and the time they spent solving the quizzes. The data were gathered from two sources, (1) the LMS Canvas and (2) Echo360, a lecture capture platform widely used among undergraduate courses to stream lectures and facilitate lecture recordings and other educational materials. The reports from both data sources were merged, and the students' activity with the learning materials (videos and slides) was linked with the students' quiz submissions. To answer the research question *How do the high achievers use the educational material provided to get better grades?*, the students were classified as high achievers if their final grade in the course was at least 80 out of 100, and non high achievers otherwise.

Significant differences were found between both groups. Firstly, high achievers not only got higher grades in both the course and the quizzes, they also spent significantly more time solving the quizzes compared with non high achievers. That difference could be explained by various causes, for example, the extent the students over-analysed their answers before submitting, or the extent they used external material such as notes, slides, or recordings while solving the quizzes. In our study, we found a positive relationship between the time the high achiever students spent solving the quizzes and their access to slides and lecture recordings. Regarding the access to lecture captures, high achievers showed higher levels of watching activity consistently throughout the course: (1) before starting the quiz, (2) while solving the quiz, and (3) once the quiz was submitted. Whereas similar results were obtained from analysing the slides viewing activity, no differences were found related to downloading the slides.

In addition, as the slides were provided through both platforms, the merged analysis allowed us to realise the platform preferences of high and non high achievers. Non high achievers, in contrast to high achievers, highly prefer to access the slides only through the LMS Canvas instead of Echo360. This may either be because they find more convenient the use of the LMS to access and interact with the slides, or because they were not used to or found the other platform more complicated or confusing. To address the latter, teachers using the learning platform in their courses to provide lecture recordings and other educational material should put more emphasis on providing the students with enough information about the learning platform to facilitate its adoption. Moreover, students would also benefit from consistency in the platforms used for teaching (López Flores, Óskarsdóttir, et al., 2022).

Our conclusions could be contrasted with research investigating other elements of learning related to engagement, and self-regulation behaviour in similar educational settings. Examples of such elements are lecture attendance records, discussion forum interactions, or activity in other educational platforms. In line with previous studies investigating varied ways of students' course participation and educational material use (Jovanović et al., 2021), our research shows high achievers' usage patterns were more consistent as the course progressed. In contrast, non high achievers show a work avoidance behaviour; which describes students who strive to maximise success through minimum effort (Harackiewicz et al., 2008). Students that apply the work avoidance mindset to their studies, generally get lower grades (Brdar et al., 2006; King and McInerney, 2014). Our analysis also allowed us to examine how the high achievers usage of the learning materials changed. Those changes were primarily found in the ratio of lecture capture watched while solving the quizzes and after the quiz submission. The results of our analysis suggest high achievers learn to benefit from the course material available by heavily relying on the lecture captures to solve the quizzes and get higher grades. Despite the potential drawbacks of depending on the educational material provided to solve assignments, we consider this behaviour could be, under some circumstances, considered as beneficial for the students. Interacting with the course content while solving the quizzes, promotes that the students' to become familiar with the class syllabus, its content, and topics. Those interactions would increase the students' understanding of the class content, positively impacting their performance in other elements in the assessment structure, such as assignments, projects and exams.

Among the limitations of this study, in this course setting, the teacher allowed the students to take as much time as needed, and access the material while solving the quizzes intending to encourage them to make the most of the course content before the assignments and final project submissions. However, this course setting might prevent our findings from being generalised to other courses where the assessment structure does not allow such interactions with the learning material. Another limitation to this approach relates to the technical difficulty of merging the databases. Despite both platforms have relatively straightforward access to the data, the permits needed to download the reports, and their complex structure could make difficult for researchers and universities to extend their research on learning analytics to include more than one educational platform. Moreover, as the use of technology to support teaching and learning processes increases, the amount of data available and the complexity to store, manage, and analyse the data also increase. These restraints advocate for implementing new methodologies and algorithms, closing the gap between learning analytics and information systems (Deeva et al., 2021; Willermark et al., 2022).

Our results not only highlight the importance of considering all the educational platforms that are available to the students instead of limiting the analyses to the LMSs only, but also show the students select the platforms that better fit into their learning preferences. However, their selection might not be always the most suitable. Furthermore, it is recommended that the students receive guidance regarding the platforms they choose to rely on while studying. In order to better support the learners in regulating their learning processes, it is necessary to gain a deeper understanding of such self-regulated learning processes (Matcha et al., 2019; Saint et al., 2020). Future work of this research relates to the replication of this analysis to other courses that use the educational platforms in similar ways. However, in this research, the approach is more important than the findings. This approach can be applied to different educational settings, courses from different fields, and taught using different teaching modalities.

In conclusion, integrating the two learning platforms was helpful to gain a better understanding of the differences between high and non high achievers regarding the use of lecture recordings and slides to get better grades. High achievers learn to make the most of both learning platforms and showed consistent engagement levels with the educational material as the course progressed. In contrast, non high achievers showed lower levels of engagement during the last two weeks and relied mostly on the LMS. Accordingly, our results point towards the value of extending the LA research on students' self-regulation by considering more than one data source. Such integration, as we have demonstrated, provides relevant data to investigate the evolution of students' learning processes.

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