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Student interaction with a virtual learning environment: an empirical study of online engagement behaviours during and since the time of COVID-19.

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Student interaction with a virtual learning environment: An empirical study of online engagement behaviours during and since the time of COVID-19

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***Abstract*—This paper presents an experience report of online attendance and associated behavioural patterns during a module in the first complete semester undertaken fully online in the autumn of 2020, and the corresponding module deliveries in 2021 and 2022. The COVID-19 pandemic of 2020 resulted in a sudden move of most university teaching online, at a global and large-scale level. This, combined with the need to maintain "business as usual" resulted in new levels of student engagement data for largely unchanged pedagogical processes. Engagement data continued to be gathered throughout the subsequent, phased return to face-to-face and hybrid learning, although at a lesser level of granularity. The wealth of student engagement data gathered during this time allows quantitative insights into how student behaviour continued to adapt during and after the enforced online learning during the COVID-19 pandemic. The anonymous subjects of this case study are computing science students in their final year of undergraduate study. We examine their engagement with the virtual learning environment, including engagement with recorded lecture material, attendance in online sessions and engagement during in-person labs. We relate this to both the students' final grades and the content of the module itself. A number of conclusions are drawn based on this empirical data, relating to observations made by staff and pedagogical theory. There was a moderate, but significant, correlation between engagement in synchronous online lecture sessions and grades during thelockdown phase, but the strength of this correlation has reduced in subsequent years as normality has returned. From monitoring behaviour in online sessions down to minute-by-minute accuracy, it can also be seen that some students strategised their engagement based on sessions they perceived to be most directly contributory to their assessment, placing little value on live guest lecturer sessions. During enforced online learning, the most successful students, on average, engaged with less repeat content than less successful students, instead apparently utilising lecture recordings to "catch up" with missed live lectures.**

***Index Terms*—online learning, empirical study, attendance, attainment**

I. INTRODUCTION

The global COVID-19 pandemic elicited a big change in the delivery of higher education. In the United Kingdom and many other countries worldwide, academic institutions faced an immediate and sudden switch to online teaching and assessment [1], which has been referred to as "Panic-gogy" [2]. This continued into the 2020-21 academic year. Classes and labs, originally intended to be delivered in person, had to switch to largely online delivery methods for teaching and assessment. Online learning and teaching methods were adopted by students and academics who may have had little practical experience in an online learning environment. The disruption continued in the 2021-22 academic year with online learning, some of it supplemented with socially distanced labs whenever lockdown conditions eased. During this time, many course syllabi remained consistent as instructors struggled to bring some stability to an environment of change [3]. In 2022, something of a return to normality was observed, however some benefits of hybrid/blended learning were maintained, matching some of the expectations of academics around the world [4].

This COVID-19-induced switch to online learning also facilitated access to previously unrecorded attendance data. Traditionally, attendance on campus was recorded using a paper register which the student could personally sign, or have signed on their behalf, potentially physically abandoning the session shortly after. Replacements for this have often focused on a single point of attendance recording [5], [6], where students actively self-report their attendance. Online attendance records give a much finer granularity. Although attendance in an online session does not necessarily mean full engagement, it might be taken as an indicator of commitment to a module.

Learning analytics have been recently highlighted as some of the key indicators of student engagement in a time when physical interaction is restricted [7]. In truth, though, it has long been expected that learning analytics and educational data mining will form an integral part of pedagogical research in the near future, with analysis of student behaviours and prediction of student performance proving to be popular areas [8]. The data mining of learning metrics has been used previously to predict student grades using decision trees and attendance was found to be influential [9]. In the past, in-person attendance has been shown to correlate positively with student attainment in computing science modules [10] and in general [11]. However, "in-person" can be split into two factions: "physically present" and "synchronously engaging". This work examines factors relating to the latter to attempt to quantify the importance of synchronous engagement both with and without the possibility of physical presence.

A pre-COVID study showed that advance knowledge of lecture recording can negatively impact physical attendance and thus student attainment [12]. This subject is still open for debate, however, and a previous study contradicts this [13]. It could be hypothesised that students who previously attended lectures in-person on campus, might be less motivated to attend online lectures at their time of delivery. After all, their physical surroundings would not change whether they attended synchronously or watched the recording later; both would simply be a computer in their home. The only advantage to attending a synchronous online session would be the interaction opportunity and internet connection issues may also make downloaded recordings more appealing than a live stream. There has been some work that shows that, during COVID-related lockdowns, online lectures were better attended than pre-lockdown in-person counterparts [14], however it is unclear whether this was simply an effect of limited social interaction opportunities during COVID, and whether higher attendance in online classes would have continued after COVID.

In this paper, we explore the issue of attendance in an online environment. We look at behavioural patterns of students interacting with synchronous online sessions and asynchronous recordings over the course of three diverse academic years, and how these relate to different attainment levels. We examine students' initial response to online learning and analyse whether this has remained consistent beyond the immediate effects of COVID. In a new age where pedagogical technique is evolving and practitioners must decide which aspects of the newly-discovered, necessity-driven techniques to maintain, it is important to ensure that these decisions are data-driven and based on solid foundations. This paper aims to provide a quantitative record of the student response to pedagogical decisions based on necessity. The main goal of this paper is provide a complete record of the effects of pedagogical change over the time of COVID-19 and the subsequent return to the "new normal".

II. Learning environment

One module over three academic years was examined for this paper (summarised in Table I): CM4125 Data Visualisation. The module was hosted by Robert Gordon's School of Computing in Aberdeen, Scotland, and took place over a ten week semester (with additional coursework submission weeks) from September to December 2020, and subsequent deliveries in the same months in 2021 and 2022. In 2020, the module involved weekly, online, synchronous sessions consisting of some lecture/lab content and some open question time. In 2021, the online lecture was maintained but supplemented with a 2 hour, socially-distanced lab on campus. In 2022, the social-distancing restrictions were removed, but the online lecture was maintained. All synchronous sessions (online and in-person) were timetabled between 9am and 5pm on a weekday. In each case, the completed module was worth 15 SCQF credits (equivalent to 7.5 ECTS) and delivered alongside three other modules of equal value. The students enrolled in the module were undergraduates in the final year of a four year programme. Like many modules running during this time of upheaval, the module content remained largely consistent across all three years, with consistent curriculum, learning outcomes and assessment methods. The assessment was an open-book coursework.

In 2020 and 2021, online sessions took place via BlackBoard Collaborate Ultra Online Classroom (BBCollaborate) [15] and attendance and recording data was gathered using the report information there. Some content was recorded during the live session and made immediately available via BBCollaborate with links on the module CampusMoodle page. The BBCollaborate report provided a record of students accessing these links. In 2022, due to a change in institutional policy, BBCollaborate was replaced by Zoom, the logs providing similar granularity of student access data. The Zoom recordings were made available via links on CampusMoodle, which recorded student engagement with these resources. Students were also directed to various resources for self-study, and although CampusMoodle recorded their interaction with these resources, in this analysis, this data was only used as a means of monitoring engagement within in-person labs. A single access of the module Moodle page during a timetabled in-person lab was taken to mean that a student engaged with that particular lab.

During 2020, live online sessions followed a general rule of approximately one hour of lecture time followed by two hours dedicated to lab completion, lab demos and/or coursework time with the immediate availability of tutors in the online session. This reflected the learning format that the students were accustomed to from their prior time on campus. In all modules, labs involved analysing data and writing code, and the students were free to utilise university resources remotely (while online), in person (while on campus) or complete the labs on their own computers. In all cases, students were required to access lab content via CampusMoodle.

The assessments for all module runs consisted of two submissions with deadlines as detailed on Table I, but students were free to submit work prior to deadlines. Work was submitted to CampusMoodle dropboxes (one for each submission) with a 30 minute grace period after the submission deadline to allow for any off campus technical difficulties. Passing grades were A-D inclusive, and non-submissions from enrolled students were also recorded.

In 2020, the lectures in session 5 and 9 involved guest speakers, session 10 involved a short revision lecture and time given over to allowing students to complete their assessment.

TABLE I: Module summary

Year	Students	Submission 1	Submission 2	Lectures	Labs
2020	118	Week 5	Week 10	BBCollaborate	Online (BBCollaborate)
2021	73	Week 5	Week 10	BBCollaborate	In-person (distanced)
2022	65	Week 6	Week 11	Zoom	In-person (normal)

These guest lectures were provided as recordings in 2021 and 2022.

All students enrolled on the module had participated in on-campus higher or further education prior to pandemic-enforced distance learning. All data is fully anonymised.

III. Data analysis and results

Table II shows the overall grade distribution for across all deliveries of the module, from 2020 through to 2022, after first marking. Some grades have been subject to appeals or may have been altered later as part of the quality assurance procedures in place at Robert Gordon University. The grade distribution reveals that the majority of students in each cohort passed the module, with many receiving good passes of an A, B or C for the module. There was a very low percentage of failing (E) grades in 2020 and 2021, and because of this, the engagement statistics for this group might be more prone to extremes. No F grades were recorded during the period. There was a reasonably high and consistent proportion of non-submissions (N/S), and this might be attributable to a combination of pandemic conditions and the procedure for resits. During 2020, students had to become their own, self-reliant systems administrators and deal with setting up and maintaining their own software and equipment, in some cases for the first time. Some may have had trouble submitting due to internet connectivity issues. Some will have had made the decision that submitting in lockdown conditions would not necessarily benefit them. Moreover, a number of students either opted to temporarily suspend their studies during COVID or else were subject to mitigating circumstances that saw them eligible to attend the module in 2021. This hangover may have contributed to the number of non-submissions remaining high. In 2022, the non-submission effect of the pandemic has shown signs of subsiding, with more students feeling able to submit, but with the proportion of D and E grades increasing. Some of this increase may simply be because of the decrease in cohort size: one student failing is a larger percentage of a smaller cohort. Noticeably, there is no definite upward trend in higher grades over the years.

TABLE II: Grade distributions (%)

Grade	2020	2021	2022
A	26.3	27.4	26.2
B	33.2	37.0	26.2
C	22.9	21.9	20.0
D	7.6	4.1	13.8
E	1.7	1.4	7.7
N/S	8.5	8.2	6.2
Pass Rate	90.0	90.4	86.2

TABLE III: How many sessions were attended?

Grade	2020 $mean \pm std$	2021 $mean \pm std$	2022 $mean \pm std$
A	8.1 ± 1.6	6.2 ± 3.4	6.2 ± 2.2
B	6.6 ± 2.8	7.6 ± 2.7	5.2 ± 2.9
C	6.6 ± 2.9	6.4 ± 3.1	4.5 ± 2.7
D	4.3 ± 2.9	6.7 ± 0.6	3.6 ± 2.4
E	9.0 ± 1.4	7.0 ± 0	6.4 ± 3.6
N/S	3.3 ± 3.2	3.5 ± 2.6	2.8 ± 3.2

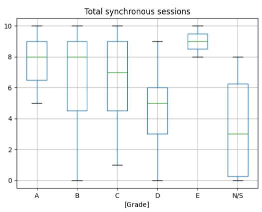
TABLE IV: Significant Pearson's correlations between activity and grade

Activity	Pearson's	p-value
2020 total synchronous online sessions	0.4167	<0.01
2021 total synchronous online sessions	0.2316	0.0487
2022 total synchronous online sessions	0.2878	0.0201
2020 total unique lecture sessions	0.446	<0.01
2021 total unique lecture sessions	0.2583	0.0274
2022 total unique lecture sessions	0.268	0.0309
2021 distanced labs attended	-0.0045	0.9702
2022 labs attended	0.2622	0.0349

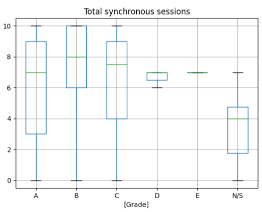
A. Live sessions or recordings?

Table III summarise the grade group attendance in online synchronous sessions. Table /reftable:Pearsons shows the correlations of the more significantly correlated activities. Pearson's correlation coefficient was chosen for this because the grades are ordinal. For 2020, there is a significant, moderate correlation between grade and the number of online synchronous sessions attended of 0.4167. For 2021 it is 0.2316 and for 2022 it is 0.2878, a reduction to a weak correlation. Fig. 1 shows these relationships as a box plot. What emerges implies that the initial jump to online learning in 2020 was more successful in terms of student engagement among the top performing students than the subsequent hybrid learning in 2021. Students who got higher grades were more likely to have attended synchronous online sessions. In general, members of the A grade group of 2021 attended fewer synchronous online sessions than their direct peers in the year before and the year after. Meanwhile, the B, C and D groups show somewhat similar behaviour across all three years, with B students generally engaging more than C students, generally engaging more than D students. Although the group of E grade students is relatively small, the statistics show that these students are likely to engage consistently with synchronous sessions. The groups of students who ended up with a "No Submission" (N/S) grade overall consistently engage in fewer online sessions than their peers, and Section III-B explores this further.

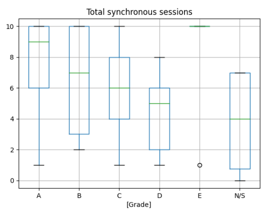
With the availability of recordings, it was possible that students either had legitimate reasons for not attending (e.g.



(a) 2020

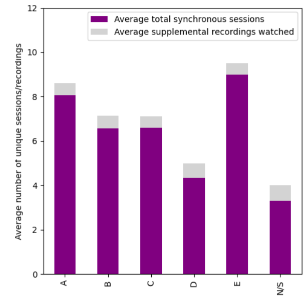


(b) 2021

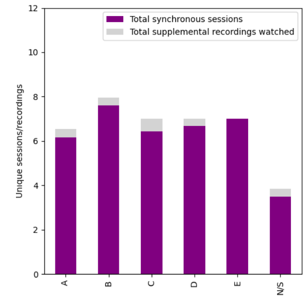


(c) 2022

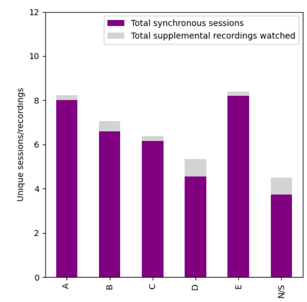
Fig. 1: Synchronous session attendance by grade



(a) 2020



(b) 2021



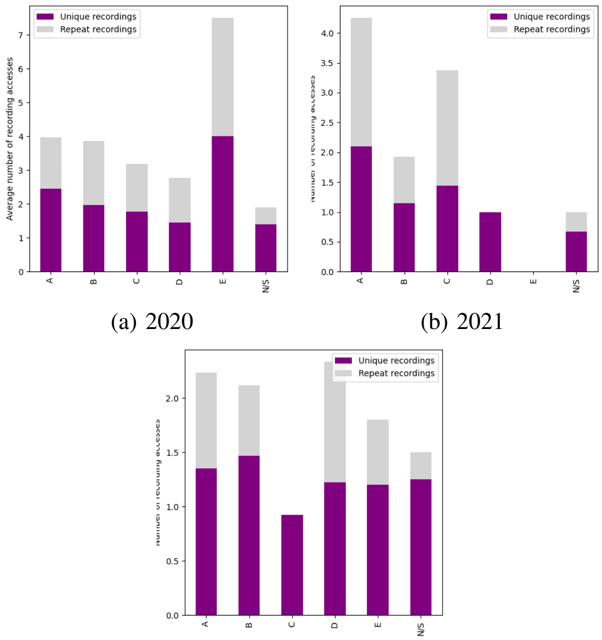
(c) 2022

Fig. 2: Average synchronous sessions topped up with recordings

employment) or were strategically opting out of synchronous sessions but using lecture recordings to catch up online. Figure 2 shows the average number of interactions with unique lecture sessions split by grade. An "interaction" is taken as a student either joining an online session or accessing a recording from a session they did not attend. It can be seen that, although students did tend to use recordings to "catch up" on sessions they have missed, missed sessions were in the minority, and students preferred to attend live online sessions at their scheduled time. For 2020, the Pearson correlation coefficient for the combination of unique session engagement (whether synchronously or asynchronously) was 0.446 ($p<0.01$), higher than for synchronous sessions alone. For 2021, it is apparent that the top performing group of students were not catching up with recorded content. The E grade group show engagement with more unique course content than all other groups in 2020 and in 2022, however this result may be skewed due to the small number of individuals in this group, and none of the correlations to do with recordings and grade were significant.

Figure 3 show the total number of recording accesses split into recordings accessed for the first time and repeat recording accesses. No data was available on how long students interacted with recordings after access, so accesses could imply that the student simply clicked on the link multiple times but watched little. It is clear, however, that students did access recordings of sessions that they attended in person. In 2020 and in 2021, the average number of recording accesses is similar amongst students obtaining grades A and C, with all three top grade groups accessing far fewer recordings in 2022 than in 2020. In [13], it was reported that students achieving higher grades had accessed more recordings, with a weak correlation coefficient of 0.139 between recording accesses and grade. Our results show a similar, but insignificant weak correlation. During enforced online learning in 2020, the Pearson correlation coefficient for recording accesses and grade was 0.109 (p=0.2401). In 2021, it was 0.1871 (p=0.1129) and in 2022 it was very weak at 0.0649 (p=0.6067). In the E grade group, as with the synchronous session data, small numbers of students accessing small numbers of recordings may have skewed the results and affected the significance. Overall, the number of recordings accessed across all grades was much smaller in 2022 when in-person labs returned. From this it can be inferred that the availability of recorded content was more important when physically in-person sessions were limited. With the return of full, physically in-person labs, recording accesses dropped and they were less correlated with grade.

Socially distanced labs were introduced in 2021 and on-campus (non-socially-distanced) labs were reintroduced in 2022. Figure 4 shows the distribution of engagement with module content on the virtual learning environment during scheduled, on-campus labs and table IV shows the correlation with grade and significance. Similar to the distribution for online lecture engagement, it can be seen that in addition to low engagement with recordings and online lectures, the top performing group of students in 2021 did not engage with socially-distanced labs either. This group of students may have simply learned an effective self-sufficiency in terms of their learning during the initial pandemic conditions in their previous year of higher education. Figure 4b shows that the E grade students engaged fully with the return of "normal" labs. Socially distanced lab attendance in 2021 did *not* correlate with grade (from table IV Pearson correlation coefficient -0.0045) and even reduced the correlation coefficient and significance (0.1622, p=0.1703) when labs were counted as

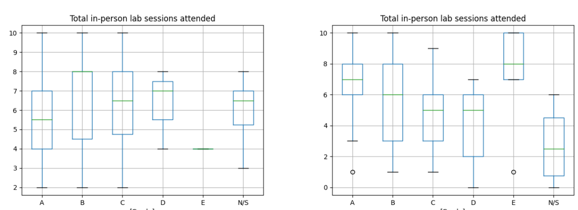


(a) 2020 (b) 2021

(c) 2022

Fig. 3: Average recording accesses (clicks on recorded material links). Note: different y-axis scales

a "unique session". This might evidence that the students who attended socially-distanced labs either did not benefit from them, or were taking direct action to obtain support from tutors with limited impact on their grade.



(a) 2021 (b) 2022

Fig. 4: Engagement with module content during in-person lab sessions

B. Attendance behaviour patterns in live sessions

Figures 5 and 6 show the proportion of students of each grade in attendance 30 minutes before, during, and 30 minutes after each synchronous session delivered during online learning. Students could join a BlackBoard Collaborate session up to 30 minutes before the official start time, and during 2020 were advised to show up 15 minutes early. Fig. 5 details every minute of the available online synchronous sessions, including the recorded lecture sessions (pink) and the allocated online lab time. The graphs for 2021 and 2022 detail only the lecture content. In 2022, the first two lectures of term were delivered as recorded material, but for the purposes of the graph, any student who engaged with module content during that week's in-person lab has been marked as present. All graphs have labelled, vertical lines indicating submission deadlines. These graphs are all plotted retrospectively: the students would not have known their module grades while they were attending the sessions. The exception to this being that if they did not submit anything to the first assessment deadline, then they could expect to receive a "N/S" grade overall, assuming they had full understanding of the grading process. Visualising the attendance data in this way displays the patterns of student behaviour in synchronous sessions, which have a moderate but significant correlation with grade.

The graphs in Fig. 5 and Fig. 6 confirm the anecdotal feeling among module co-ordinators that attendance drops off as time goes on, in terms of both individual sessions and the semester as a whole. Across all years and grades, the average attendance (in terms of the percentage of the grade group) in the first week is 84.4 ± 17.2. This drops to 48.4 ± 24.3 by the 9th week. Anecdotally, this matches the behaviour seen in-person and observations by [6] with students attending fewer sessions and leaving labs earlier as the semester goes on. Perseverance in attendance, however, can be seen in the patterns, particularly in the higher grades. Students obtaining higher grades tended to maintain attendance in synchronous online sessions throughout the 2020 semester, and they tended to stay slightly longer in sessions, too (Fig. 5). This behaviour could be described as a practical demonstration of perseverance of effort [16]. However, similar patterns can also be observed in the E grade group who also seem to be consistent and thorough attendees, although this effect may be overstated due to the relatively small number of students. The most important issue arising from this observation is that students receiving a failing grade are not completely disengaged, but they would be difficult to identify and monitor in an online environment.

Another pattern relating to perseverance of effort is that of non-submitting students in 2020, Fig. 5. Their attendance drops off starkly around the time of the first submission, despite the fact that feedback was only available 4 weeks after coursework submission. This pattern is also visible in 2021 (Fig. 6a) but not in 2022 (Fig. 6b. The difference between 2021 and 2022 delivery is the socially-distanced labs. Struggling students might avoid submission rather than fail [17] and disengage as a form of protecting themselves from failure, therefore avoiding the first assessment submission of the module. There is a possibility that the isolation of lockdowns exacerbated this effect and that the availability of scheduled, in-person labs provided a degree of protection. Students felt able to make the first submission and attended later sessions with the intention of making the second submission, too. Identification of such a behavioural pattern in absences early in the semester might facilitate early intervention and reduce the number of non-submissions. The other plausible reason for this behavioural pattern in 2022 is that students missing *either* coursework submission will receive a non-submission grade overall. However they will only have to resit missing components. Students in 2022 may have missed the

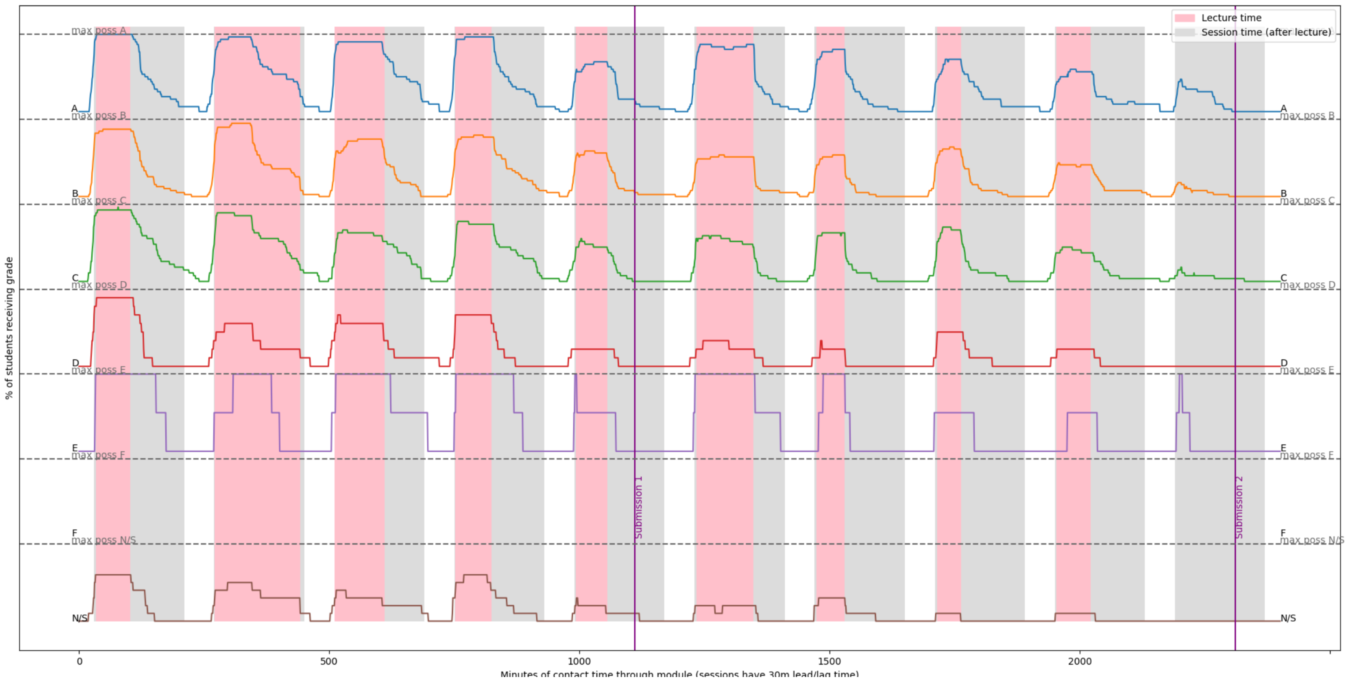


Fig. 5: Minute-by-minute student attendance in lectures and labs, delivered online, 10 week semester, autumn 2020

first coursework submission but submitted the second in the knowledge that it would minimise their resit effort.

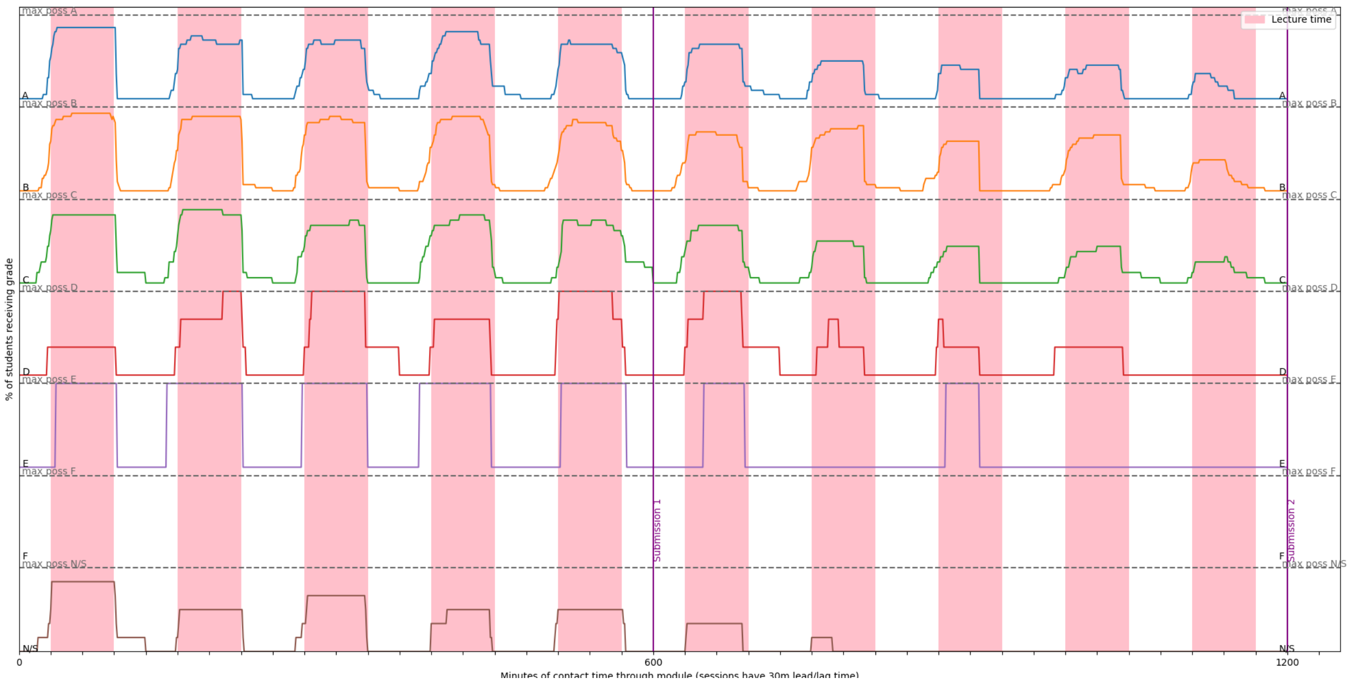
In 2020, Fig. 5, it can be seen that many students across all grades were sufficiently engaged during online lectures that they could easily identify when the lecturer had switched from content delivery (recorded) to question and answer sessions. Students attended for live content delivery during synchronous online sessions even though they knew a recording would be available later. However, a significant number of students left sessions once they had inferred that content delivery was complete, generally at the conclusion of the session recording. Students did not seem to value open forums on BlackBoard Collaborate that took the place of labs. Alternatively, it might be that students did not want to leave while the recording was in progress. The in-person equivalent of this behaviour might be leaving immediately after the lecture and not staying to attend the lab. From this, it can be inferred that many students do not see the value of witnessing questions raised by their peers in an online session and prefer to tackle practical work independently, or at a later time. Alternatively it might be that social pressure and the idea that their exit might be announced in the online environment dissuades students from leaving while the recording is in progress. The patterns in the second week of 2020 (Fig. 5), however, imply that this is not the case. In this week, the recording overran into the lab and students were still aware of when lecture delivery was over, with a synchronised drop off of students on the call after approximately an hour.

Another student behaviour that is evident from these graphs is strategic attendance. Fig. 5 evidences that the sessions with guest speakers in weeks 5 and 9 had noticeably lower attendance across all grades. It could be argued that week 5 also corresponds to a submission week, and students have simply made the logical decision to work on their coursework rather than attend a guest lecture. This supports the idea that "students will study what they think will be assessed" [18]. 2021 saw guest lecture content only in week 9 where already low attendance will have camouflaged any effect, but a drop in attendance is not observed. The guest lecturer content was moved to be "extra content" in 2022, where a recording was made available on the Moodle page.

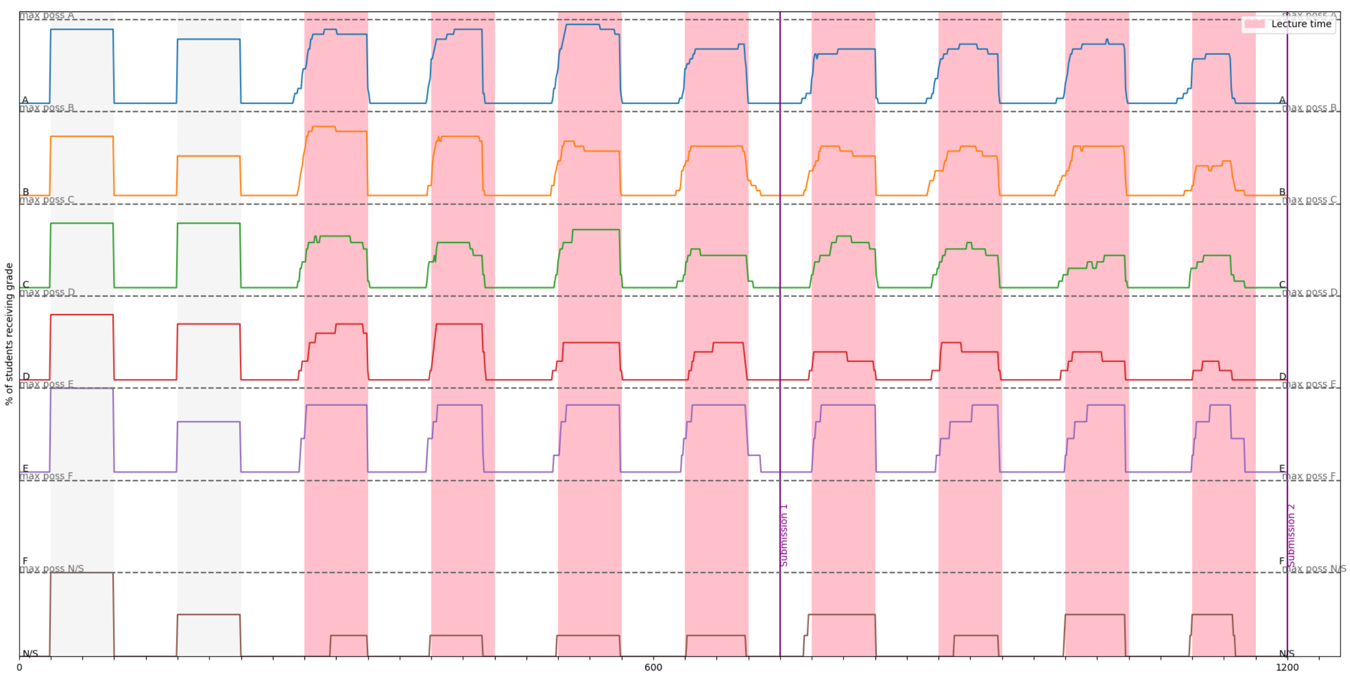
IV. Limitations

Both BlackBoard Collaborate and Zoom attendance reports offer only the time of the first join, the time of the last leave, total time in the session and the number of joins for each student. In Figures 5 and 5, the number of joins and any time between the first join and last leave spent out with the session has been disregarded. Data analysis showed that the average time between the first join and the last leave that was spent outwith a live session was less than 2 minutes. However a small minority of students in the 2020 cohort spent as much as an hour or more outwith the session between their first join and last leave. In some cases, experience suggests at least some of this time may have been spent one-on-one with a module tutor on a different communication platform, and was therefore still spent engaging with module material.

As is usual for university timetables, students from all cohorts were also involved in another three modules running concurrently with these modules. Assessment deadlines for these concurrent modules occurred at various times from week 5 onwards. Some of the associated workload for this might



(a) 2021



(b) 2022

Fig. 6: Minute-by-minute student attendance in live online lectures, 10 week semester

have impacted synchronous session attendance in our observed module.

The learning metrics used in this paper are limited to the virtual learning environment controlled directly by Robert Gordon University. More specifically, the learning metrics in this paper relate directly to live session attendance (BBCollaborate and Zoom), recording accesses (via BBCollaborate and Moodle logs) and clicks on Moodle material (Moodle logs). Student use of online materials outwith the module content cannot be measured but must not be overlooked as a source of learning.

V. Conclusion and future work

The global COVID-19 pandemic brought significant challenges in the delivery of computing science education. However, the transition to online learning has also provided the teaching community with a detailed data source. Passively generated learning metrics provide an objective measure of student action and provide valuable insights into what students value and what contributes to student learning.

Our analysis has shown that learning metrics can be used to identify student behaviours relating to attendance and attainment. Students forced online by COVID-19 initially retained some of their in-person attendance behaviour patterns but quickly developed some new ones and put them into action during a time when pedagogical upheaval was ongoing. Initial enthusiasm for online learning in 2020 waned in 2021, and engagement in socially-distanced labs was relatively poor. Instead, more able students in 2021 may have developed a degree of independent learning, enabling them to look at resources outwith the measurement capacity of our current learning metrics. Visualisation of passively generated online learning metrics helps to make these patterns discoverable.

Given that many of the correlation coefficients reported in this paper are weak-to-moderate, it can be said that the learning metrics reported herein are insufficient on their own to predict student attainment in a rapidly changing pedagogical environment. Some of the relationships are statistically significant, however, and this confirms that monitoring student engagement is an important technique. That said, the observations reported here have already been used to improve module content (for example, the rescheduling of guest lectures) and continue to be an inspiration for data-driven pedagogical decisions.

Our future work will examine whether these metrics can be integrated with modern machine learning techniques to discover whether individual students' levels of attainment can be predicted from early data and ultimately enhanced by timely interventions and improvement of teaching best practices.

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