How Does Student Access to a Virtual Learning Environment (VLE) Change During Periods of Disruption?

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Higher Education often faces disruptions to teaching due to wider events, such as industrial action by staff or the recent COVID-19 pandemic (Li et al., 2022). Digital learning tools (such as Virtual Learning Environments, VLEs) can be used to support teaching and learning processes reducing the impact of disruptive events. This case study, compares student VLE behaviour across three consecutive cohorts featuring two "typical" university semesters (2016 and 2017), and one semester (2018) which featured industrial action. Learning analytics from students' activity on the VLE system analyzed. Findings show that high- and middle-performing students tend to increase their use to compensate for the lack of teaching, whilst lower-performing students reduce their access possibly due to lower levels of self-efficacy and self-regulation. These findings suggest that educators need to consider how VLEs could be designed to support students when learning should be delivered through an asynchronous online learning environment. For example, educators should consider designing VLE spaces that promote flexibility, and supporting self-regulation, whilst also providing clear guidance on structuring learning activities.

Keywords: virtual learning environment (VLE), asynchronous, case study, disruption, strikes, self-regulation, learning analytics, student behaviour

INTRODUCTION

Since their introduction over 25 years ago Virtual Learning Environments (VLEs), also known as Learning Management Systems (LMS), have enabled students studying courses to access information asynchronously and/or synchronously. This use of a VLE results in institutions developing large stores of data on student learning behaviour, in the form of VLE traces. Unfortunately, due to the difficulty with collating and analyzing such data, this information is rarely used to inform data-driven decisions (Dawson et al., 2010). By 2003 almost 86% of Higher Education institutions were using them to support their courses (Weller et al., 2003), a figure rising considerably over the years to encompass the majority of university-taught courses. A VLE system (i.e., Blackboard, Moodle, Canvas) also supports teachers to deliver a blended learning approach allowing them to upload course materials/assessments, interact with their students, and even gather statistics regarding student participation and engagement (Limniou & Smith, 2010). Allen and Seaman (2010) define blended learning as any course where between 30% to 80% of the instruction takes place online. Courses using a VLE to support blended learning, have been shown to have a small but positive effect on student learning, particularly in STEM-based subjects (Vo et al., 2017). Examining a move to blended learning, Zacharia (2015) examined 29 different online activities and found that while the graded discussion board accounted for 37% of the variance, just 2% of the variance was accounted for by files viewed. A potential explanation for this finding is that in many cases the dominant use of a VLE is that of content delivery (McFadyen & Dawson 2012). However, it remains unclear how much VLEs influence student learning/grades, as the previous studies have tended to focus on changes within a learning system rather than how students change their behaviour when presented with a change partway through the semester (i.e., move from a blended approach to asynchronous online teaching). One way of further exploring this issue is by examining how students' interactions with VLE platforms may change when they lost the face-to-face teaching elements of a blended approach due to a sudden teaching disruption (i.e., industrial action and lockdown), therefore relying only on online activities.

The recent global pandemic in 2020 "forced" teachers and students to move to emergency remote teaching (Hodges et al., 2020 where many educators utilized a range of teaching delivery process, including distance synchronous lectures. These could be delivered through online conferencing technologies (i.e., Zoom and Microsoft Teams) supported by supplementary online material (Bilal et al., 2021), or asynchronous teachings where recorded material was uploaded to a VLE system (Zeng & Wang, 2021; Khobragade et al., 2021). In addition to the move to online learning during a lockdown, students also needed to grapple with many other challenges and confounding factors to their learning such as illness, work responsibility, competence with online learning systems, and even navigating how to do laboratory work online (Bilal et al., 2021). Such asynchronous teaching delivery processes were also implemented over the industrial actions which took place in the middle of the second semester of the 2018 academic year across UK universities (Birgfeld, 2018). This current case study examines data regarding student VLE use in 2018 when staff members at the institution were striking, and the two years prior when teaching was conducted as normal - thereby seeking to isolate the effects of VLE use when all other factors are the same.

A VLE can be used in a variety of ways from a simple repository of materials up to a fully developed blended learning environment, however either case the VLE will tend to be one of the central focus points of a course, with students accessing materials and learning through the VLE and university course systems rather than on external sites and tools (Dawson, 2010), or social media (Limniou, 2021). As such VLE data traces can be an important way of researching student behaviour within the digital environment. Such student VLE data can be used in multiple ways but is mostly used to identify at-risk students and to explain variance in learning outcomes.

In a meta-analysis of over 7000 students, Wolff et al., (2013) found that the use of a VLE combined with continuous assessment was the best predictor of student dropout, suggesting that monitoring of early use of VLEs could be harnessed to target potentially at-risk students. Additionally, a wide body of previous studies has also examined the predictive value of VLE use for academic performance using various metrics such as hits (clicks on the online learning material/collaborative tools), discussion board posts, and time spent on the VLE platform (e.g., Gašević, et al., 2015; Gašević, et al., 2014). One of the most common measures of VLE use in the literature is that of hits on course material. However, these demonstrate an inconsistent picture with studies finding a range of effects from several significant correlations (e.g., Chen & Jang, 2010), through to no significant effect on course material (e.g., Yamaguchi et al., 2019). Another measure of VLE engagement that has been used within research is that of the overall time spent by students accessing the VLE, however at the best overall time, shows a weak relationship with student results, regardless of the breadth and diversity of material examined (Biktimirov & Klassen, 2008; Crampton et al., 2012). Other studies have explored the number of hits, with similarly varied pictures. Baugher et al., (2003) suggested consistency of access (as a proxy for distributed practice) was the most important factor for predicting outcomes, while other studies have suggested that access immediately before an exam is more important than access at other times throughout the semester (Levy & Ramin, 2012; Park et al., 2016; Rienties & Toetenel, 2016).

The variance in findings regarding the best predictive measure of performance could also fluctuate between course topics. Finnegan et al., (2009) found that there was no single significant predictor shared across all disciplines, and although some variables were identified as significant predictors for individual disciplines the same effect was not apparent when the disciplines were combined. Indeed, a similar finding from Gašević, et al., (2016) led them to conclude that to create effective and successful predictive models for individual courses it is essential to include instructional conditions and pedagogical factors (such as whether activities are formative or summative. Therefore, it's important to consider how students interact with different kinds of learning activities.

A review of the literature suggests that some of the individual elements hosted within VLEs could differentiate and contribute to the overall effect on performance. Elements such as stream capture (lecture recordings) and associated PowerPoints have been found to make little difference to grades (O'Bannon et al., 2011; Smeaton & Keogh, 1999; Leadbetter et al., 2013). While the provision of graded discussion boards (Green et al., 2018; Moore & Gilmartin, 2010) and formative assessment (Kavadella et al., 2012; Ćukušić, et al., 2014) both show significant associations with grade. Both discussion boards and formative assessments can be used to demonstrate engagement with the subject being studied. As Nieminen et al., (2004) illustrated, student choices on what, how, or even when to engage in the study were closely connected to students' levels of self-regulation. A student who prefers external regulation is likely to rely more heavily on teachers, peers, or study materials, something Khobragade et al. (2021) identified as one of the large barriers to online learning during the pandemic. Equally, weaknesses are also present in student study strategies, such as massed practice and surface learning strategies which can lead to poor educational outcomes (Metcalfe & Kornell, 2005), as can a lack of engagement with course materials (Davis & Graff 2005). Failing and students passing with lower grades have been shown to use VLEs less than successful students (Sclater et al., 2016; Morris et al., 2005). Indeed, a recent study by Gašević, et al., (2016) found that a 10% increase in access led to a 2% rise in students' average marks, with one of the most reliable indicators of student failure being changes in one's VLE behaviour (Wolff et al., 2013). Unlike face-to-face elements of a course, one's access to a VLE is largely based on asynchronous and independent study habits.

Although asynchronous online elements allow the students to work at their own pace and time, there is often little guidance on how to make the most of these learning opportunities (McKenzie et al., 2013; Tan et al., 2021). As a result, some students may lack the self-regulation and motivation needed to complete tasks independently, particularly when academic support is absent (Wolters et al., 2005 Martin et al., 2020). This self-regulation in turn is closely linked to academic achievement (Broadbent, 2017). Examining study behaviour Blasiman and colleagues (2017) found that students intended to use a variety of study techniques across the course but ended up relying on surface strategies and mass study a few days before the exam. This finding is also echoed by Kornell and Bjork (2007), who concluded that most student behaviour tended to be based on immediate goals such as passing exams, while long-term retention and learning did not feature in their considerations. As a result, students may choose to prioritize immediate concerns over longer-term learning outcomes.

Sansone et al., (2012) argue that learning through a VLE may be particularly sensitive to self-regulatory trade-offs because there is little external monitoring to guide student choices. A compounding factor to these difficulties is that longitudinally students often maintain the same (un)successful behaviours. Persky (2018) measured changes to students learning strategies over time and found that these remained relatively constant throughout the course, suggesting students were not good at adapting their study strategies to changing circumstances. As a result, if students are using successful strategies, then it is likely they will continue to use these successfully, equally those students using less effective learning strategies may struggle to understand how to improve. A further compounding difficulty can be when disruptions and changes occur partway through a course. Such changes can be on an individual level (e.g., illness, poor mental health, etc) or a course-wide level (such as faculty strikes, or the recent global pandemic).

When teaching staff goes on strike it is common practice to provide learning materials online so that students are not as disadvantaged as they may otherwise be due to an absence of direct teaching. Typically, these include recorded lectures from previous years and other material designed to allow students to study independently. This provision may in part explain why studies such as that by Jacquemin et al., (2020) found no significant effects of strikes on final grades, while older studies found small, albeit significant effects (Grayson, 1997; Belot & Webbink, 2010; Aremu et al., 2015). However, these studies did not explore student VLE behaviour in depth and did not consider the fact that some students may be more successful than others at switching to using technology as a substitute for face-to-face activities (Bos et al., 2015). Most of the studies discussed above consider student behaviour under normal circumstances and to date, no study appears to have explored student behaviour and how this may, or may not, change during strike action by educators. Based on the literature discussed above and the contrasting findings within it, the current study seeks to examine the following hypotheses:

H_1: *Does overall hit consistency accurately predict students' grades?*

H_2: *Is accessing stream capture and course PowerPoints associated with the final module grade of students?*

H_3: *Does student behaviour (including hit consistency) change during years with strike action, compared to years with no strike action?*

H_4: *Does student behaviour change (or not) during strikes compared to their behaviours in periods with no strike action?*

H_5: *If behaviour does change, does this have any effect on student outcomes?*

METHODS

The current study used data traces taken from three large cohorts of first-year undergraduate students and their VLE activity within a biological psychology module presented in their second semester. The University, based in the Northwest of England, uses Blackboard for its VLE platform. Within the module space, students can see information arranged in a file structure with each week's teaching having a separate folder. Each week's folder contains a recording of the lecture capture, two copies of the lecture PowerPoints (one complete and one with spaces to aid active notetaking), and various other miscellaneous materials, such as supplementary videos and extra information. The module also has a discussion board; however, this is only used by a small subset of students (less than 10%) and is not graded. A brief examination of comments on the discussion board showed these were mostly variations on "will this be on the exam", therefore data from this material source was not analyzed further in this study. To encourage distributed practice four low-stakes quizzes (worth 5% each of the overall module mark) are presented in weeks 3, 5, 7, and 9 of a 12-week semester. The content was covered in the first 10 weeks, with week 11 devoted to a revision lecture and the final week being reserved for independent revision.

Data were collected over three consecutive years (2015/16 – 2017/18) by a non-teaching member of staff (a student researcher). The data consisted of the number of hits on each kind of material, with the number of hits per day recorded. This data was then grouped into weekly totals for each of the ten content weeks, the one revision lecture week, a two-week independent revision period, and finally 3 weeks of Easter holidays, as well as pre and post-course variables (both of which showed little access, with only a few students accessing the materials either before or after the course teaching dates). In the academic year, 2017/18 staff took strike action, which impacted the module under consideration during weeks 5, 6, and 7.

All usage data was downloaded immediately following the completion of the final module exam across each of the three years. Participants were informed about the study before the start of the semester via email and verbally within lectures at various points across the module, they were made aware that their study results would not be linked to their academic records, and were also able to withdraw their data should they choose to do so. This study was approved by the University's ethics board (IPHS-2015-2016-411).

Since combined honours students at the University take this module as part of their second-year schedule these students were removed from the analysis, as were any who dropped out before the final module exam. Any student who failed and subsequently re-took the module had only their first attempt recorded. The resulting dataset consisted of records from 1340 students (roughly 33% from each cohort). Data from overall access to weekly folders were used. To examine the individual elements more specifically, hits on lecture capture recordings and access to either of the PowerPoint documents were analyzed. To measure overall hit consistency access to each of the 10 weeks of content, folders were converted to binary values (not accessed = 0, accessed = 1), creating 14 overall hit consistency values (10 teaching weeks, 1 two-week revision period, access pre-course, access post exam and access during three-week Easter break). These were then added together to create a variable of access to each of the content folders at each of the time points.

RESULTS

As the aim of this study is to explore students' learning behaviour and patterns regarding the use of VLE in a UK University, the collected data was mainly related to students' grades on online assessments and hits on VLE learning material (i.e., stream capture and PowerPoint presentations). This study also considers the impact of industrial actions, as part of the students' study disruption. Data on exam results were significantly different for the 2017/18 cohort, compared to the other two cohorts, with these students scoring significantly more than those in previous years, on both the final module exam ($p=.003$) as well as in three out of four of the online tests ($p> .05$). These scores were subsequently transformed into Z scores for the analysis of examining effects on grades.

Overall Hit Consistency

A simple linear regression b(showed that overall hit consistency on weekly folders explained approximately 3.3% of the variance in the four weekly MCT grades (adjusted $R^2 =.033$, $F (14,1325) = 4.82$, $p <.001$). (see appendix for figure 1) Specifically, access to course material was positively associated with access in week two (β .068, $p=.045$), week three (β .078, $p=.044$), and negatively associated with access in week 10 (β -.088, $p=.019$). It was also significantly associated with access before the start of the course (β .070, $p = .011$), during the converged revision weeks (β .083, $p=.012$), and following the exam (β .092, $p=.001$). Access during the Easter break was not significant ($p=.201$), nor was access during week one ($p =.864$), week four ($p=.095$), week five ($p=.276$), week six ($p=.117$), week seven ($p=.110$), week eight ($p=.495$), or week 9 ($p=.850$).

Further regressions were conducted to examine the effects of each of the four biweekly tests. In the case of test one (which was provided in week three, covering material from the start of the course through to week three), the model explained approximately 3.7% of the variance in grades (adjusted $R^2 = .037$; $F(4,1335)=13.90$, $p<.001$). Specifically, access in week two was significantly associated with grade (β .64, $p =. 46$), as was week three (β .143, $p<.001$), however access before the start of the course ($p =.189$) and in the first week ($p=.640$) were not significant.

The remaining three tests occurred every fortnight, showing a similar pattern of results. Access to course material was significantly related to the second test (given in week five) explaining 1.3% of the variance (adjusted $R^2= 0.13$; $F(2, 1337)=10.10$, $p <.001$). Specifically, week four was not significantly associated with test results ($p=.704$) however access in week five was significantly associated (β .114, $p =.001$).

Test three (given in week seven) explained 4% of the variance ($R^2 =.040$; $F(4,1337) = 28.76$, $p <.001$). Again, week six was not significantly associated with grades ($p=.996$), whilst week seven showed a small but significant grade association (β. 203, $p <.001$). Finally, test four again showed a similar pattern, the overall model was significant explaining 1.5% of the variance (adjusted $R^2 =. 15$; $F (4,1335)=13.90$, $p<.001$), with week eight showing no association ($p=.257$) and week nine showing a significant association (β. 148, $p<.001$).

Effects of PowerPoint and Recorded Lecture Stream Capture

To explore the effects of individual course elements, data relating to hits on lecture PowerPoints and lecture stream captures were assessed individually and summed as above creating a hit score. (See appendix for figure 2 & 3) Note, since other elements such as supplementary videos and information sheets were not consistent across the module, data relating to these material types were not included in the following analysis. When examining each of the course elements individually the model final? grade performs better than overall access predicting 18.1% of the variance in multiple-choice marks (adjusted R^2 =.181; F(27, 1310)= 91, p<.001).

Specifically, access to PowerPoints across the three cohorts was only significant in week six where it showed a slight negative association (β.-62, p<.001), whilst in weeks eight (β.104, p = .001), and nine (β.077, p=.011) a positive association was noted. All other weeks showed non-significant associations: pre-course (p=8.52), week one (p=.081), week two (p =.126), week 3 (p=.242), week four (p=.412), week five (p =.195), week seven (p =.209), the Easter holiday break (p=.753), week 10 (p=.535,) revision weeks (p=.882), and post-exam (p=.255).

The stream capture of lecture recordings showed significant associations in weeks two (β. 081, p=.039), week five (β.161, p<.001), week six (β.186, p<.001), and week seven (β. 0.95, p=.001). The remaining weeks were not significantly associated with multiple choice scores at pre-course (p=.351), week one (p=.484), week three (p=.342), week four (p=.555), during the Easter break (p = .114), week eight (p=.060), week nine (p=.856), week ten (p=.340), revision weeks (p=.352), and post-exam (p=.242).

When examining each of the four tests a similar pattern was seen. The overall access for test one of the model explained approximately 1.9% of the variance, R^2= .019, F(8,1329)=4 .276, p<.001, specifically PowerPoints in weeks one (β. 086, p = .004), week two (β. 083, p=.013) and week three (β. 092, p =.007) were significantly associated with test one while Stream Capture was not associated with grades in week one (p=.539), week two (p =.369) or week three (p =≥369) equally access before the start, showed no association with grades for either PowerPoints (p =.994) or Stream Captures (p=.996).

Test two also showed a significant association between access and skills explaining approximately 2.3% of the variance, R^2= .023, F(4, 33)=8.707, p<.001, with only access to PowerPoints in week five showing a positive association (β. 091, p=.035). PowerPoint access in week four was not significant (p=.730) and neither was Stream Capture access in either week four (p=.278) or week 5 (p=.265). Conversely, Stream Capture access was significantly associated with results for test three explaining approximately 7.4% of the variance, R^2= .074, F(4, 1333)=8.707, p<.001, with both week six (β. 134, p< .001) and week seven (β. .268, p< .001) seeing significant associations. Access to PowerPoints was not significant in week six (p=.488), or week seven (p = .344). Finally, in the case of test four, the model explained 6% of the variance in grades, R^2=. 60, F(4, 1333) =8.707, p<.001, with both PowerPoint in week eight (β. 088, p = .003), and week nine (β. 123, p <.001), as well as Stream Capture in weeks eight (β. 77, p =.007), and week nine (β. 167, p<.001).

The Effects of Striking

To assess whether student behaviour changed during the 2018 strikes, the hit values were converted to ratio values of pre-strike (weeks 1-4), strike (weeks 5-7), post-strike (weeks 8-10), and revision weeks (weeks 11 and 12) to explore the differences between students access across the weeks. 83 students in this cohort's sample did not access the VLE during teaching weeks 1 to 10 and were removed from the analysis. The same transformation was also applied to individual items (PowerPoint and Stream Capture). To examine the effects of VLE access on student's grade boundary a 4 x 2 between subjects MANOVA, using grade boundaries (1^{st}, 2:1, 2:2, 3^{rd}, and fail) and strikes (strike/no strike action) showed an overall significant main effect of grade (Pillai's trace =0.40 and year Pillai's trace =.160).

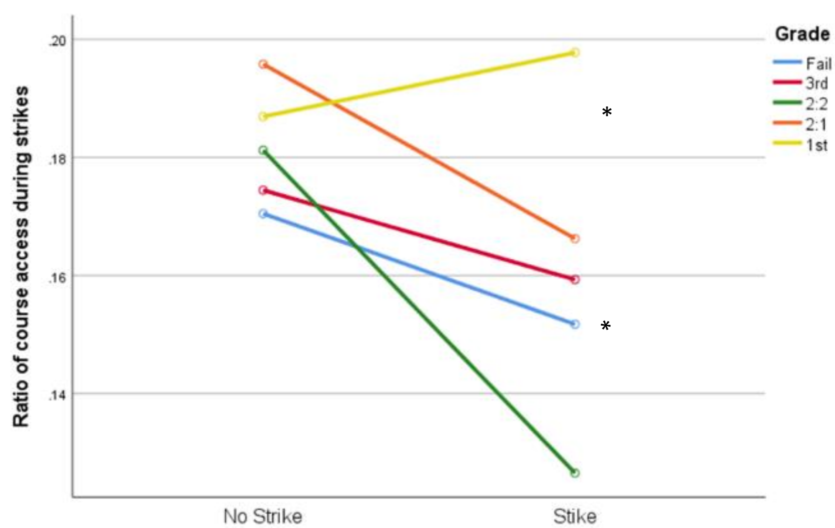
TABLE 1
MANOVA BETWEEN GRADE AND STRIKE YEAR ON OVERALL HITS TO THE VLE

Grade boundary	
Pre-Strike	F(4,1330)=2.48, p=.042, η^2 =.007
Strike	F(4,1330)=8.02, p<.001, η^2 =.024
Post-Strike	F(4,1330) =5.41, p<.001, η^2 =.016
Revision	F(4,1330)=5.41, p<.001, η^2 =.016

Strike Year	
Pre-Strike	$F(4,1330) = 109.12, p < .001, \eta^2 = .076$
Strike	$F(4,1330) = 14.87, p < .001, \eta^2 = .011$
Post-Strike	$F(4,1330) = 109.12, p < .001, \eta^2 = .078$
Revision	$F(4,1330) = 122.47, p < .001, \eta^2 = .084$

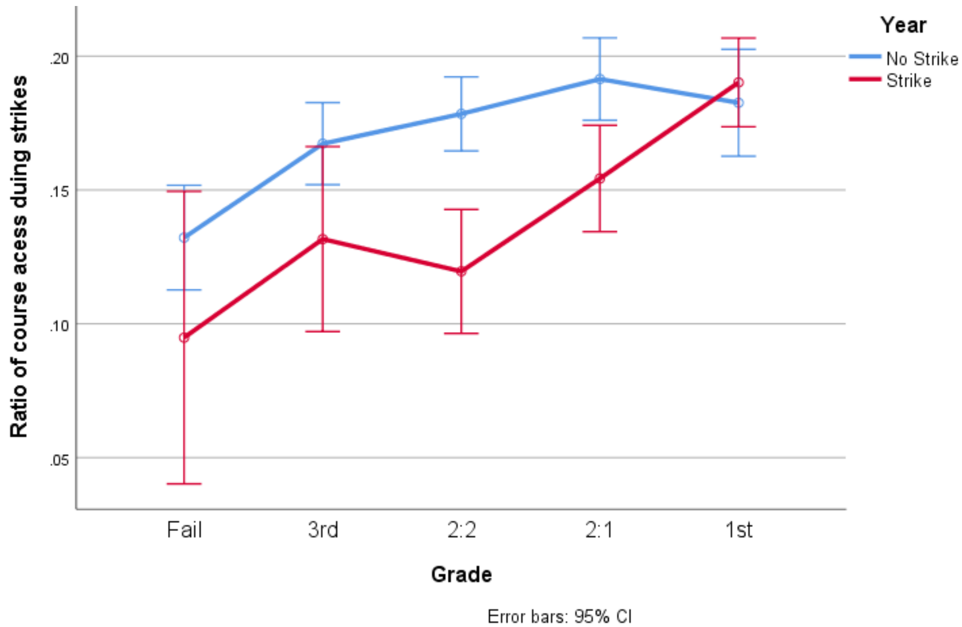
Additionally, there was a significant interaction between grade boundary and year during the strike weeks, $F(4, 1330)=3.238, p=.012, \eta^2 = .010$, however, there were no other significant interactions (prestrike p=.136, post-strike p=.603, and revision p=.605). Specifically, T-tests comparing strike years with no strike years showed first-class students accessing the VLE considerably higher during strike weeks, however, this difference was not significant (p=.551). Conversely, students in other grade boundaries accessed the VLE significantly less during strike weeks showing a significant difference in access levels for those at the 2:2 level ($T(337) = 4.70, p<.001, d= 0.58$), and the 2:1 level ($T(312) = 2.91, p = .004, d = 0.32$). Both failing (p =.327), and 3rd class students (p=.161) showed no significant difference in access level (see Figures 4 and 5).

FIGURE 1
INTERACTION BETWEEN STRIKES AND STUDENT GRADE DURING STRIKE WEEKS (N = 1340)



* Significant differences

FIGURE 2
LINE CHART SHOWING OVERALL ACCESS TO VLE FOLDERS SPLIT BY GRADE (N = 1340)



The Effects of Striking Across Cohorts

Access to PowerPoints across the cohorts was also examined using a 4 x 2 between subjects MAONVA. Results showed an overall significant main effect of grade (Pillai's trace =.100 and year Pillai's trace =.039 and an overall interaction Pillai's trace = .023). Additionally, there was a significant interaction between grade boundary and year during the prestrike weeks ($F(4,1330)=4.04$, $p=.003$, $\eta^2=.006$) and during the revision weeks ($F(4,1330)=8.33$, $p=.003$, $\eta^2=.012$). However, both strike ($p =.111$) and post-strike were not significant ($p=.080$). Results showed similar findings to those for overall access, first-class students did not access significantly more materials before the strikes ($p=.406$), but did access significantly more materials during the revision weeks ($T(586)=2.28$, $p=.023$, $d=0.19$). Students working at a 2:1 level did not access significantly different amounts of materials either pre-strike ($p=.689$) or during revision weeks ($p=.406$). Equally, students working at the 2:2 level showed no significant difference in access before strikes ($p=.351$), or during the revision weeks ($p=.351$). However, for students at the third-class level, the pattern of access shows no significant difference at pre-strike ($p=.525$), but during revision weeks they accessed significantly fewer materials ($T(484)=3.15$, $p=.002$, $d=0.34$). Equally, for students failing the course, access to materials at pre-strike was lower, and approaching significance = .051, whilst access during revision weeks was higher ($T(44.73)=4.227$, $p<001$, $d=0.721$). Finally, access to stream-captured lecture recordings was explored through a 4 x 2 between subjects MANOVA showing an overall significant main effect of grade (Pillai's trace =.095 and year Pillai's trace =.346). There was a significant interaction between grade boundary and year only during the prestrike weeks ($F(4, 1330) = 2.66$, $p = .031$, $\eta^2 = .008$), whilst for strike ($p = .833$), post-strike ($p = .898$), and revision ($p = 0.680$) weeks findings were not significantly different (see Figure 3).

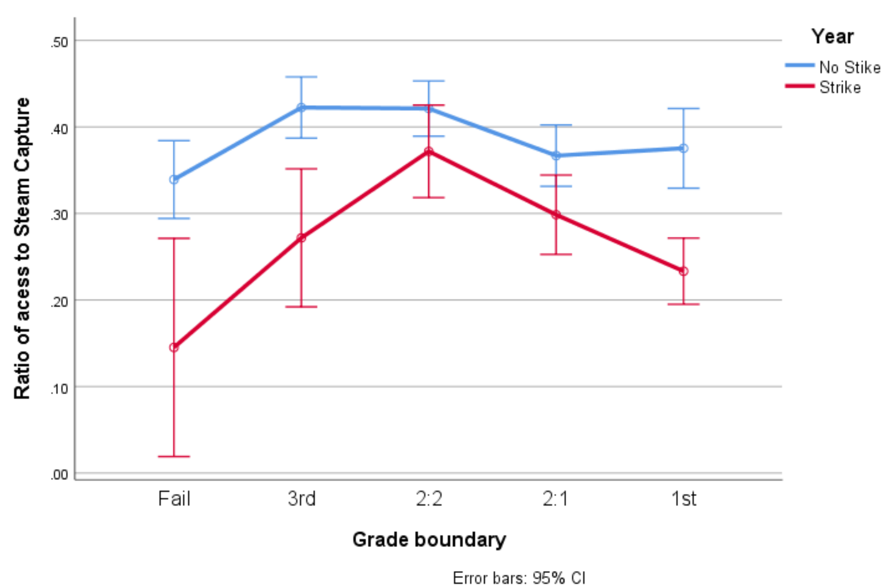
TABLE 2
MANOVA BETWEEN GRADE AND STRIKE YEAR ON POWERPOINT ACCESS

Grade boundary	
Pre-Strike	F(4,1330)=2.48, p=.042, η^2=.007
Strike	F(4,1330)=2.48, p=.053
Post-Strike	F(4,1330)=5.413, p<001, η^2=.016
Revision	F(4,1330)=50.05, p<.001, η^2=.180.
Year	
Pre-Strike	F(4,1330)=3.12, p=.012, η^2=.010
Strike	F(4,1330)=1880, p<.001, η^2=.027
Post-Strike	F(4,1330)=11.61, p<.001, η^2=.016
Revision	F(4,1330)=19.42, p<.001, η^2=.028

TABLE 3
MANOVA BETWEEN GRADE AND STRIKE YEAR ON STREAM CAPTURE

Grade boundary	
Pre-Strike	F(4,1330) = 1.23, p=.063
Strike	F(4,1330) = 10.47, p<.001, η^2=.310
Post-Strike	F(4,1330) = 0.73, p=.069
Revision	F(4,1330) = 6.67, p<.001, η^2=.020
Year	
Pre-Strike	F(4,1330) = 533.258, p<.001, η^2=0.286
Strike	F(4,1330) = 1.13, p=.229, η^2=.030
Post-Strike	F(4,1330) = 105.25, p<001, η^2=.073
Revision	F(4,1330) = 38.68, p<.001, η^2=.028

FIGURE 3
ACCESS TO STREAM CAPTURE SPLIT BY GRADE



DISCUSSION

The current case study sought to examine student behaviour in accessing course materials on a VLE platform both under normal and disruptive teaching conditions. The results showed students of differing abilities engaged in differing patterns of access, but all students tended to mass their access at the end of the course, just before exams. Furthermore, low-stakes quizzes whilst slightly increasing access during the weeks they were due, they did not consistently and significantly affect use.

Overall hit consistency showed that access towards the start of the course was positively associated with grades, whilst access during the final teaching week was negatively associated with grades. However, in general, regular access across the course did not significantly predict findings. Equally, although the variance explained by PowerPoints and Stream Capture recordings specifically explained more of the variance, hit consistency did not show a relationship between final module grades. Additionally, in the case of each of the four tests, the picture is varied, with access during non-test weeks being slightly lower and overall not connected with access to course materials. However, when these are examined in terms of individual PowerPoints and Stream Captures these show an increasing association with test grades suggesting that as the material becomes more complex students are accessing the material more frequently. Indeed, the results of the MANOVA show an increase (albeit a gradual one) in access to material across the course with slightly more access taking place in test weeks than non-test weeks. This coupled with the large spike in course access during revision weeks suggests a tendency for students to engage in the massed practice - a finding similar to that found by Levy and Petrulis (2012).

There are two possible explanations for this finding, firstly the variation in access to material suggests that only the most engaged students were regularly (i.e., weekly) accessing the course material. These were also the students who were more likely to access the material at other times (such as during breaks, before, and after the course). Because there were four tests presented across the course designed to encourage distributed practice, students were overall accessing the course materials on the VLE approximately every two weeks, a factor that may have moderated the findings. Indeed, it is likely that a course without such a test would show a still stronger effect of mass practice at the end of the course. The significant finding for access during the revision weeks matches other similar studies such as that conducted by You et al., (2016) showing that most students tend to focus their attention/time in the period immediately before an assessment. The significant correlation between hits during the revision weeks and grades suggests that the course design only had a limited effect in encouraging regular engagement. Taken together these findings support the previous literature finding that although hit consistency only weakly predicts overall grades, the variance predicted and its effect are minimal. Further, these findings are likely being driven by students' levels of self-regulation meaning those with higher levels of self-regulatory behaviour are also consistently more likely to engage with the course regularly. A high level of self-regulation could therefore explain the more frequent use of a VLE system, and as Carter et al., (2020) note this is a vital component to consider when designing online learning.

In examining the effects of strikes, students (except first-class ones) accessed the VLE less throughout the 2018 module. The patterns of usage behaviour highlighted above suggest that students may have accessed the VLE less in the weeks before the first biweekly test. At this point students would have been aware of the forthcoming strike and may have made a conscious decision to focus on other priorities/modules within their course such as upcoming coursework, perhaps planning to revisit the materials once the strikes had concluded. The finding that access to PowerPoint during the revision week increased for first-class students, and remained the same for those in the middle grades (2:1 and 2:2) while dropping further for failing and third-class students suggest that those working at different grade levels will respond differently to any challenges of access. Indeed, a recent study looking at Veterinary Science and Psychology student's behaviour during the recent pandemic (Limniou et al., 2021) showed a similar relationship between student use of digital tools during the lockdown and their self-regulation which in turn demonstrated an effect on grade boundaries. In considering the use of recorded lectures through Stream Capture, an unexpected finding was that this technology was used more by students in non-strike years. Although during the strike weeks, lecture recordings from previous years were uploaded, it appears that many students chose not to make use of these. It's possible that this finding could suggest that students valued live lectures over recorded ones. However, as this finding is contrary to similar studies showing that on the whole students prefer recorded lectures (especially those with disabilities and English as a second language e.g., Porter et al., 2021), it would be worth exploring this result in more detail in a future study. Overall, the findings suggest that students working at the first-class level changed their approach to the material, increasing their access, specifically accessing PowerPoints and ancillary material (such as web links or articles). At the same time, these students made less use of Stream Captures than those in the middle-grade boundaries (2:1 and 2:2) who did not appear to change their access behaviour as a result of the strikes. Finally, those at the lower end of grades (3rd class and failing) made less use of the VLE consistently throughout the course only increasing their access slightly during revision weeks. This result could potentially be explained by decreasing motivation, further exacerbated by poor self-regulation during strike action.

The overall picture presented by these findings suggests that students can be clustered according to their grade boundary and that each of these groups will respond differently to changes in the teaching environment. Although not directly measured in this study it would also appear that students who have higher levels of self-regulation find it easier to adapt to changes in teaching (such as strikes or the recent move to emergency remote teaching) by changing their study habits to most effectively make use of the material provided (Believe et al., 2021). For example, by encouraging increased access and/or accessing different types of course materials. Additionally, those who struggle with self-regulation, are likely to find independent study more difficult and when faced with no immediate need to access the material, may procrastinate, and put off access until shortly before the exam. Indeed, although the tests were worth 5% of the overall grade several students chose not to take these tests at all, in particular, several students chose not to take test 3 across all of the three cohorts studied, this could have been as they had other coursework deadlines at this time. Having said this, access to materials was not significantly different for students between strike and non-strike years suggesting that this finding may relate more to students' self-regulation levels experiencing a mid-term drop-off in engagement which then translates into reduced access to the VLE more generally.

This study has a few limitations, the design of the VLE meant that students were able to download materials in advance (except for the recorded lectures) and could have shared these by other means, thus resulting in analytics showing the student only ever accessing the VLE once. Other students will have accessed the material every time they wanted to consult it. Additionally, the system only recorded clicking on each of the materials, meaning recording engagement with the course materials was unable to be gathered. This weakness may go some way toward explaining the low effect sizes found by this study. Since VLEs have become more sophisticated the quality of available learning analytics has improved with many VLEs (e.g., canvas) providing much richer data regarding student interaction with course materials. Secondly, the current study only examined first-year students studying a single online module within a Psychology course. Specifically, our research shows this biological module to be more difficult for students without an A-level in biology and/or chemistry (Hands & Limniou 2023). As such, future studies should therefore consider comparing findings across disciplines and/or differing year groups since it is likely that both domain, study stage, and prior qualifications held by the students affected these results. Indeed, while first-year grades varied due to the strike these did not vary to the same extent as other modules for the same students in subsequent years of their degree.

The current study offers a brief overview of how basic learning analytics can highlight how students change their behaviour both according to their academic ability (i.e., grade boundary) and external changes such as a faculty strike, individual circumstances, or even a global pandemic. These findings can help inform effective learning design, highlighting the importance of encouraging regular distributed practice and supporting weaker students to increase their levels of self-regulation. Perhaps the most important implication of this study has related to the use of learning materials that students can access and work on independently in the event of a disruption to face-to-face teaching, whatever the reason behind this may be. This study demonstrates that while at least some of the disruption caused by these events can be mediated, it is not enough to simply provide materials that give the same information as a face-to-face lecture, but instead need to be redesigned for an online asynchronous audience. Current best practice suggests that flipped classroom models, short (10-20 minute) videos of material, alongside regular low-stakes assessment, works well in both online and face-to-face scenarios (provide references); thereby offering students the best possible outcomes regardless of the means of accessing learning.

REFERENCES

Allen, E., & Seaman, J. (2011). *Class differences. Online education in the United States, 2010*. Retrieved from https://files.eric.ed.gov/fulltext/ED529952.pdf

Baugher, D., Marinelli, A., & Weisbord, E. (2003). Student hits in an internet supported course: How can instructors use them and what do they mean? *Decision Sciences Journal of Innovative Education*, *1*(2), 159–179.

Belot, M., & Webbink, D. (2010). Do teacher strikes harm educational attainment of students? *Labour*, *24*(4), 391–406. https://doi.org/10.1111/j.1467-9914.2010.00494.x

Borgfeldt, M. (2018). 'Do you believe in life after work?' The University and College Union strike in Britain. *Transfer: European Review of Labour and Research*, *24*(2), 233–236. https://doi.org/10.1177/1024258918772692

Biktimirov, E.N., & Klassen, K. J. (2008). Relationship between use of online support materials and student performance in an introductory finance course. *Journal of Education for Business*, *83*(3), 153–158.

Bilal, Hysa, E., Akbar, A., Yasmin, F., Rahman, A & Li, S. (2022). Virtual learning during the COVID-19 Pandemic: A bibliometric review and future research agenda. *Risk Management and Healthcare Policy*, *15*, 1353–1368. https://doi.org/10.2147/RMHP.S355895

Blasiman, R.N., Dunlosky, J., & Rawson, K.A. (2017). The what, how much, and when of study strategies: Comparing intended versus actual study behaviour. *Memory*, *25*(6), 784–792. https://doi.org/10.1080/09658211.2016.1221974

Broadbent, J. (2017). Comparing online and blended learner's self-regulated learning strategies and academic performance. *The Internet and Higher Education*, *33*, 24–32. doi:10.1016/j.iheduc.2017.01.004

Bylieva, D., Hong, J.C., Lobatyuk, V., & Nam, T. (2021). Self-regulation in E-Learning environment. *Education Sciences*, *11*(12), 785. https://doi.org/10.3390/educsci11120785

Calamlam, J.M., Ferran, F., & Macabali, L.G. (2022). Perception on research methods course's online environment and self-regulated learning during the COVID-19 pandemic. *E-Learning and Digital Media*, *19*(1), 93–119. https://doi.org/10.1177/20427530211027722

Carter Jr, R.A., Rice, M., Yang, S., & Jackson, H.A. (2020). Self-regulated learning in online learning environments: Strategies for remote learning. *Information and Learning Sciences*, *121*(5/6), 321–329. https://doi.org/10.1108/ILS-04-2020-0114

Chen, K.C., & Jang, S.J. (2010). Motivation in online learning: Testing a model of self-determination theory. *Computers in Human Behaviour*, *26*, 741–752. https://doi.org/10.1016/j.chb.2010.01.011

Crampton, A., Ragusa, A., & Cavanagh, H. (2012). Cross-discipline investigation of the relationship between academic performance and online resource access by distance education students. *Research in Learning Technology*, *20*. https://doi.org/10.3402/rlt.v20i0.14430

Ćukušić, M., Garača, Ž., & Jadrić, M. (2014). Online self-assessment and students' success in higher education institutions. *Computers & Education*, *72*, 100–109.

Davies, J., & Graff, M. (2005). Performance in e-learning: Online participation and student grades. *British Journal of Educational Technology*, *36*(4), 657–663. https://doi.org/10.1111/j.1467-8535.2005.00542.x

Dawson, S., McFadyen, L., Lockyer, L., & Mazzocchi-Jones, D. (2010). From neural to social: Medical student admissions criteria and engagement in a social learning environment. *Graduate School of Medicine Papers (Archive)*, pp. 292–301.

Elvers, G.C., Polzella, D.J., & Graetz, K. (2003). Procrastination in online courses: Performance and attitudinal differences. *Teaching of Psychology*, *30*(2), 159–162.
Finnegan, C., Morris, L.V., & Lee, K. (2009). Differences by course discipline on student behavior, persistence, and achievement in online courses of undergraduate general education. *Journal of College Student Retention: Research, Theory and Practice*, *10*, 39–54.
Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends*, *59*(1), 64–71. http://dx.doi.org/10.1007/s11528-0140822-x
Gasevic, D., Dawson, S., Rogers, T., & Gasevic, D. (2016). Learning analytics should notpromote one size fits all: The effects of instructional conditions in predicting academic success. *The Internet and Higher Education*, *28*, 68–84. https://doi.org/10.1016/j.iheduc.2015.10.002
Gašević, D., Mirriahi, N., Dawson, S., & Joksimovic, S. (2014). What is the role of teaching in adoption of a learning tool? A natural experiment of video annotation tool use. *Submitted for Publication to Computers & Education.*
Grayson, J.P. (1999). Student hardship and support for a faculty strike. *Research in Higher Education*, *40*(5), 589–611. Retrieved from http://www.jstor.org/stable/40196374
Green, C., Eady, M., & Andersen, P. (2018). Preparing quality teachers: Bridging the gap between tertiary experiences and classroom realities. *Teaching and Learning Inquiry: ISSOTL Journal*, *6*(1), 104–125.
Hands, C., & Limniou M. (2023). Why science qualifications should be a pre-requisite for a psychology degree programmes – A case study analysis from a UK university. *High Impact Practices in Higher Education: International Perspectives*. Emerald publishing.
Hershkovitz, A., & Nachmias, R. (2009). Learning about online learning processes and students' motivation through web usage mining. *Interdisciplinary Journal of E-Skills and Lifelong Learning*, *5*, 197–214.
Jacquemin, S.J., Junker, C.R., & Cubberley, M. (2020). Does a prolonged faculty strike in higher education affect student achievement in first year general education courses? *Journal of Collective Bargaining in the Academy*, *11*(3).
Kavadella, A., Tsiklakis, K., Vougiouklakis, G., & Lionarakis, A. (2012). Evaluation of a blended learning course for teaching oral radiology to undergraduate dental students. *European Journal of Dental Education: Official Journal of the Association for Dental Education in Europe*, *16*, 88–95. https://doi.org/10.1111/j.1600-0579.2011.00680.x
Khobragade, S.Y., Soe, H.H.K., Khobragade, Y.S., & Abas, A.L.bin. (2021). Virtual learning during the COVID-19 pandemic: What are the barriers and how to overcome them? *Journal of Education and Health Promotion*, *10*, 360. https://doi.org/10.4103/jehp.jehp_1422_20
Kornell, N., & Bjork, R.A. (2007). The promise and perils of self-regulated study. *Psychonomic Bulletin & Review*, *14*(2), 219–224. https://doi.org/10.3758/BF03194055
Leadbeater, W., Shuttleworth, T., Couperthwaite, J., & Nightingale, K.P. (2013). Evaluating the use and impact of lecture recording in undergraduates: Evidence for distinct approaches by different groups of students. Computers & Education, 61, 185–192. https://doi.org/10.1016/j.compedu.2012.09.011
Levy, P., & Petrulis, R. (2012). How do first-year university students experience inquiry and research, and what are the implications for the practice of inquiry-based learning? *Studies in Higher Education*, *37*(1), 85–101. DOI: 10.1080/03075079.2010.49916
Levy, Y., & Ramin, M. (2012). A study of online exams procrastination using data analytics techniques. *Interdisciplinary Journal of E-Learning and Learning Objects*, *8*, 97–113. https://doi.org/10.28945/1730
Li, N., Huijser, H., Xi, Y., Limniou, M., Zhang, X., & Kek, M.Y.C.A. (2022). Disrupting the disruption: A digital learning HeXie ecology model. *Education Sciences*, *12*(2), 63.
Limniou, M. (2021). The effect of digital device usage on student academic performance: A case study. *Education Sciences*, *11*(3), 121.

Limniou, M., & Smith, M. (2010). Teachers' and students' perspectives on teaching and learning through virtual learning environments. *European Journal of Engineering Education*, *35*(6), 645–653. doi:10.1080/03043797.2010.505279

Lust, G., Elen, J., & Clarebout, G. (2013). Regulation of tool-use within a blended course: Student differences and performance effects. *Computers & Education*, *60*, 385–395. https://doi.org/10.1016/j.compedu.2012.09.001

Macfadyen, L.P., & Dawson, S. (2010). Mining LMS data to develop an "early warning system" for educators: A proof of concept. *Computers & Education*, *54*(2), 588–599. https://doi.org/10.1016/j.compedu.2009.09.008

Macfadyen, L., & Dawson, S. (2012). Numbers are not enough. Why e-learning analytics failed to inform an institutional strategic plan. *Educational Technology & Society*, *15*(3), 149–163.

McKenzie, W.A., Perini, E., Rohlf, V., Toukhsati, S., Conduit, R., & Sanson, G. (2013). A blended learning lecture delivery model for large and diverse undergraduate cohorts. *Computers & Education*, *64*, 116–126. https://doi.org/10.1016/j.compedu.2013.01.009

Metcalfe, J., & Kornell, N. (2005). A region of proximal learning model of study time allocation. *Journal of Memory and Language*, *52*, 463–477. https://doi.org/10.1016/j.jml.2004.12.001

Moore, N., & Gilmartin, M. (2010). Teaching for better learning: A blended learning pilot project with first-year geography undergraduates. *Journal of Geography in Higher Education*, *34*(3), 327–344. https://doi.org/10.1080/03098265.2010.501552

Morris, L.V., Finnegan, C., & Wu, S.-S. (2005). Tracking student behaviour, persistence, and achievement in online courses. *The Internet and Higher Education*, *8*(3), 221–231. https://doi.org/10.1016/j.iheduc.2005.06.009

Mou, T.-Y. (2021). Online learning in the time of the COVID-19 crisis: Implications for the self-regulated learning of university design students. *Active Learning in Higher Education*, *0*(0). https://doi.org/10.1177/14697874211051226

Nieminen, J., Lindblom-Ylänne, S., & Lonka, K. (2004). The development of study orientations and study success in students of pharmacy. *Instructional Science*, *32*(5), 87–417. https://doi.org/10.1023/B:TRUC.0000044642.35553.e5

O'Bannon, B.W., Lubke, J.K., Beard, J.L., & Britt, V.G. (2011). Using podcasts to replace lecture: Effects on student achievement. *Computers & Education*, *57*(3), 1885–1892.

Özen, E., & Karaca, N. (2021). Investigating learner motivation in online education in terms of self-efficacy and self-regulation. *Journal of Educational Technology and Online Learning*. https://doi.org/10.31681/jetol.1016530

Park, Y., Yu, J.H., & Jo, I.H. (2016). Clustering blended learning courses by online behaviour data: A case study in a Korean higher education institute. *The Internet and Higher Education*, *29*, 1–11. https://doi.org/10.1016/j.iheduc.2015.11.001

Persky, A.M. (2018). A four-year longitudinal study of student learning strategies. *Currents in Pharmacy Teaching and Learning*, *10*(11), 1496–1500. https://doi.org/10.1016/j.cptl.2018.08.012

Porter, S.G., Greene, K., & Esposito, M.C.K. (2021). Access and inclusion of students with disabilities in virtual learning environments: Implications for post-pandemic teaching. *International Journal of Multicultural Education*, *23*(3), 43–61. https://doi.org/10.18251/ijme.v23i3.3011

Rienties, B., & Toetenel, L. (2016). The impact of learning design on student behavior, satisfaction and performance: A cross-institutional comparison across 151 modules. *Computers in Human Behavior*, *60*, 333–341. doi:https://doi.org/10.1016/j.chb.2016.02.074

Sansone, C., Fraughton, T., Zachary, J.L., Butner, J., & Heiner, C. (2011). Self-regulation of motivation when learning online: The importance of who, why and how. *Educational Technology Research and Development*, *59*(2), 199–212. https://doi.org/10.1007/s11423-011-9193-6

Sansone, C., Smith, J.L., Thoman, D.B., & MacNamara, A. (2012). Regulating interest when learning online: Potential motivation and performance trade-offs. *The Internet and Higher Education*, *15*(3), 141–149. https://doi.org/10.1016/j.iheduc.2011.10.004

Sclater, N., Peasgood, A., & Mullan, J. (2016). *Learning analytics in higher education*. London: Jisc. Retrieved February 8, 2017.

Slater, S., Baker, R., Ocumpaugh, J., Inventado, P., Scupelli, P., & Heffernan, N. (2016). Semantic features of math problems: Relationships to student learning and engagement. In *International Educational Data Mining Society*. International Educational Data Mining Society. Retrieved from https://eric.ed.gov/?id=ED592725

Smeaton, A.F. & Keogh, G. (1999). An analysis of the use of virtual delivery of undergraduate lectures. *Computers & Education*, *32*(1), 83–94.

Tan, K.H., Chan, P.P., & Mohd Said, N.E. (2021). Higher education students' online instruction perceptions: A quality virtual learning environment. *Sustainability*, *13*(19), 10840. https://doi.org/10.3390/su131910840

Torres Martín, C., Acal, C., El Homrani, M., & Mingorance Estrada, Á. C. (2021). Impact on the virtual learning environment due to COVID-19. *Sustainability*, *13*(2), 582. https://doi.org/10.3390/su13020582

Vo, H.M., Zhu, C., & Diep, N.A. (2017). The effect of blended learning on student performance at course-level in higher education: A meta-analysis. *Studies in Educational Evaluation*, *53*, 17–28. doi: 10.1016/j.stueduc.2017.01.002

Weller, M., Pegler, C.A., & Mason, R. (2003). Putting the pieces together: What working with learning objects means to the educator. Paper presented at the *eLearn International Conference*. Edinburgh.

Wolff, A., Zdrahal, Z., Nikolov, A., & Pantucek, M. (2013). Improving retention: Predicting at-risk students by analyzing clicking behavior in a virtual learning environment. Paper presented at the *Proceedings of the Third International Conference on learning analytics and knowledge, Indianapolis*.

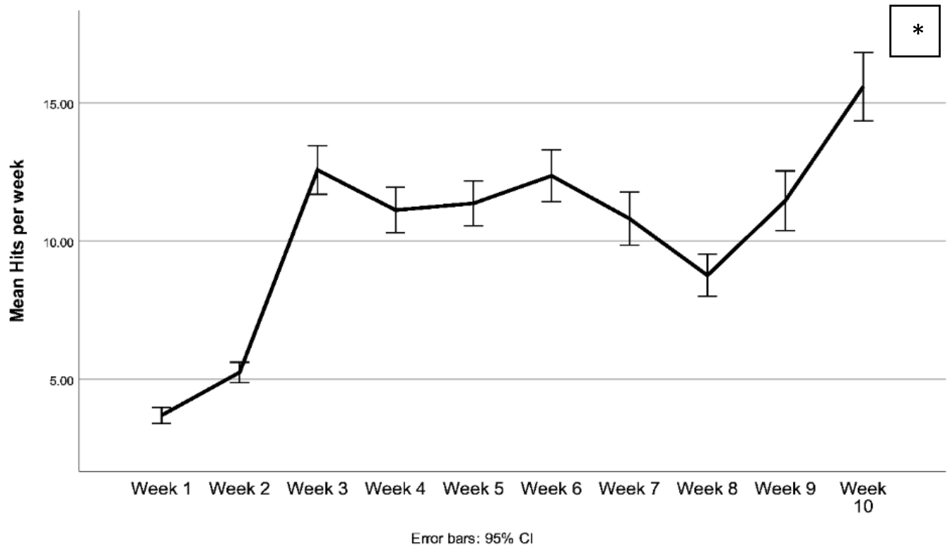
Wolters, C.A., Pintrich, P.R., & Karabenick, S.A. (2005). Assessing Academic Self-Regulated Learning. In K.A. Moore & L.H. Lippman (Eds.), *What do children need to flourish: Conceptualizing and measuring indicators of positive development* (pp. 251–270). Springer Science + Business Media. https://doi.org/10.1007/0-387-238239_16

Yamaguchi, S., Kondon, H., Ohnishi, Y., & Nishino, K. (2019). Analysis of learning activities and effects on blended lectures. *Procedia Computer Science*, *159*, 1568–1575

Zacharia, Z.C. (2015). Examining whether touch sensory feedback is necessary for science learning through experimentation: A literature review of two different lines of research across K-16. *Educational Research Review*, *16*, 116–137. https://doi.org/10.1016/j.edurev.2015.10.001

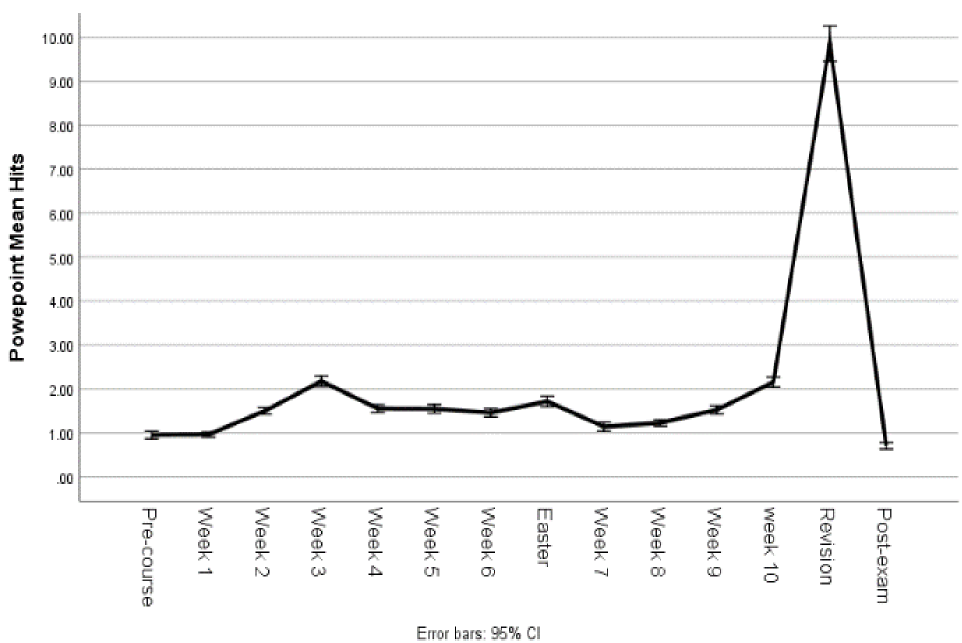
Zeng, X., & Wang, T. (2021). College student satisfaction with online learning during COVID-19: A review and implications. *International Journal of Multidisciplinary Perspectives in Higher Education*, *6(*1), 182–195.

APPENDIX 1: LINE CHART SHOWING MEAN HIT CONSISTENCY ACROSS THE MODULE'S TEACHING WEEKS



*(Mean Hits during revision period =62.8)

APPENDIX 2: LINE CHART SHOWING MEAN HIT CONSISTENCY FOR POWERPOINT ACCESS ACROSS THE MODULE



APPENDIX 3: LINE CHART SHOWING MEAN HIT CONSISTENCY FOR STREAM CAPTURE ACCESS ACROSS THE MODULE