Profile Analysis of Hourly, Daily, and Weekly Student Access to Online Asynchronous Courses

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Recent global events have led to an increase in the delivery of higher education in an asynchronous online format. These changes have impacted students' ability to schedule their lives around their education. This study investigates trends in student access to online asynchronous courses. This study utilized learning analytics data from the learning management system for thirty-eight online asynchronous communication courses taught by twelve different faculty members at a large research university in the southwestern United States. A total of 1,384 students were involved in the study. Profile Analyses indicate clear non-linear trends for time of day, day of the week, and week of the semester in student course access. Results indicate those trends vary significantly from a no-effect condition by level of course and gender of student across multiple courses.

Keywords: teaching modalities, student access, course management, learning management systems

INTRODUCTION

Recent changes in higher education due to the global COVID-19 pandemic have raised awareness among students and faculty regarding the possibilities of divergent modes of course delivery. These changes have been noticed by communities both within and outside higher ed. Research into these changes has increased in recent years (see Granic, 2023; Stone, 2022).

According to Yeboah (2022), roughly half of the students surveyed had little to no experience with online learning platforms before the COVID-19 pandemic. These online learning options are likely to grow due to the experience that instructors gained in the rapid transition to online learning during the COVID-19 pandemic (Tate & Warschauer, 2022). Although faculty perceive themselves as content matter experts, they do not perceive themselves as trained in creating accessible online materials (Lowenthal and Lomellini, 2023). The creation of content and course design aimed at online delivery can affect student learning outcomes and, ultimately, their academic success. Additional study is needed to determine relationships between observed navigational behavior in online courses and individual student differences (Çebi et al. (2023).

REVIEW OF LITERATURE

Background

A systematic search of the literature through the *Web of Science* database using the search terms "student AND online AND access" limited to January 1, 2022, through January 1, 2024, yielded 1,971 results.

Duplicate articles from the previous study were eliminated, resulting in a total of 68 articles reviewed. Of those articles, 55 were determined to be relevant for the current study. These studies are organized by subtopics including articles focusing on digital access, time and day of access, and student characteristics.

Digital Access

According to Werang and Leba (2022), students' lack of access to technology is the most significant factor contributing to a lack of engagement in online learning environments. Access to broadband Internet was the most significant variable influencing access to online course materials (Gu, 2022). COVID-19 demonstrated uneven access between countries based on their progress in developing information and communication technology infrastructure (Hlatshwayo, 2022). Post COVID-19, online education has continued to develop as a means of reaching students otherwise not attending school in both the for-profit and non-profit educational sectors. However, online education still has development pains. For example, according to Smith et al. (2023), online education is associated with lower retention and graduation rates in for-profit and not-for-profit educational sectors.

These effects may be due to differences in digital access. Adanir et al. (2022) found that poor access to computers was related to lower levels of cognitive engagement, however, behavioral engagement was associated with higher levels of academic achievement through mobile devices. Interestingly, Battestilli et al. (2023) found the strongest level of participation in course activities in online asynchronous courses compared to in-person, synchronous, and HyFlex (student chooses the modality) courses. On the other hand, Ruth et al. (2022) found that students in online courses appreciated the ability to participate that would not be available to them in traditional face-to-face settings. These same students also reported the benefits of time flexibility for course activities in the online modality. (Ruth et al., 2022).

There are developments in online education that are beneficial to students. According to Kanetaki et al. (2022), use of a single platform for delivery of online content assists both students and instructors in staying on task. These developments have not necessarily been linear or smooth across the board. Manzoor and Bart (2022) argued that the COVID-19 pandemic exacerbated the gap in access to learning resources for marginalized communities. For example, during the COVID-19 pandemic, student engagement in course content decreased even when the transition to fully online delivery was relatively smooth (McKenna et al., 2022).

According to Fabian et al. (2022), students forced to study online during the COVID-19 pandemic discovered new pressures, including home-based distractions and unplanned workspaces, which affected their ability to engage with course materials. However, only a minority of students had quiet spaces to study for online classes during the COVID-19 pandemic, and most had household chores to distract them (Pérez-Villalobos et al., 2023). Reed et al. (2022) found that students from low-income families were more likely to have more home-related obligations and more difficulty accessing online content compared to their peers. Likewise, Roshid et al (2022) found that Bangladeshi students from underprivileged backgrounds did not have uninterrupted Internet access allowing them to participate in online education. However, students from these low-income backgrounds and those who work are more likely to transition to online education (Sánchez-Gelabert & Elias, 2023). These students are also more likely to drop out (Sánchez-Gelabert & Elias, 2023).

According to Bell, Bartimote, Dempsey et al. (2022), students experience issues with privacy and physical space, as well as interruptions, when working in an online space. Some negative effects of online interaction included decreased motivation to engage with others. However, Lebens (2022) and Rivers (2023) found that a majority of students perceived either no impact or a positive impact on their access to online course materials during the COVID-19 pandemic. Students choose online learning for four reasons, flexibility in access, continuing their education, the ability to interact with their peers, and the ability to express their opinions through discussion forums (Stephani et al., 2023).

According to Farley and Burbules (2022), course design greatly enhances student participation. Instructors can influence student engagement with content by utilizing multiple interactive strategies including weekly tasks and activities, discussion boards, and unit-specific digital tools (Muir et al., 2022). Moosa (2022) found that utilization of asynchronous online peer-to-peer discussion forums facilitated engagement and learning. Grant and Oerlemans (2022) also found that the number of instructional videos accessed positively influenced students' final grade outcome in an undergraduate statistics course.

According to Antasari (2022), students' offline access skills such as defining and articulating information needs significantly influence their intention to access online information. However, a lack of these skills may contribute to behaviors in an online class which work against meeting student success goals. To be sure, students may be distracted by non-course related online content. Koay and Poon (2023) argued that cyberslacking behavior (accessing online sites unrelated to course tasks) is difficult to detect by instructors without the use of cameras. However, cameras are not relevant for asynchronous courses, unless employed during virtual office hours. According to Brown et al. (2023), student increased their online engagement when nudged by instructor intervention through online course messaging.

During the COVID-19 pandemic, students in India spent between four and six hours daily online attending university classes, but a significant difference was found between students attending premier institutions where they may have had previous online course experience and students at other institutions without such experience (Dayal & Pratibha, 2023). Student engagement in face-to-face courses is quite distinct from student engagement in synchronous online courses, with students in online courses displaying fatigue from extended use of cameras (Murphy et al., 2022). According to Cenka et al. (2022), students who access online course material more frequently perform better compared to students who access less frequently.

Time and Day

Recently, researchers have begun to utilize learning analytics from the Learning Management Systems to determine student engagement of online course materials. Through a systematic review of the literature, Ahmadi et al. (2023) discovered that twenty-one articles mentioned usage of LMS log-in data with only two articles mentioning log-in and usage data of the Blackboard LMS specifically. Additionally, the authors found only one article which described data collected about number of course views and time spent viewing in Blackboard. Ahmadi et al. (2023) found that such research using learning analytics data is still emerging.

According to Bulut et al. (2023), learning analytics data including student access hits can be used to create predictive models for student success. Utilizing Blackboard data, Al-Zahrani and Alasmari (2023) discovered that students using non-mobile devices (computers) tend to engage more course materials for longer periods of time than students using mobile devices, whereas students using mobile devices access more often but for shorter periods of time.

Le et al. (2022) examined total student access hits (clicks) per week across four STEM disciplines (Biology, Chemistry, Mathematics, and Science) for a sixteen-week semester prior to the COVID-19 pandemic and suggested that observed differences between disciplines may be a function of assessment deadlines and degree of online interactivity built into the course. According to Laparra et al. (2023), student access to online course materials is time-of-day dependent, although their study found a bi-modal distribution with peak times between 11am and noon, and again around 5pm.

Koh and Daniel (2022) found that student engagement in online courses is influenced by their participation strategies including regularly scheduled online access, online discussions, and seeking support through virtual office hours. Additionally, students who go to bed and wake up early experience fewer online education barriers than those who go to bed after midnight and wake up after noon (Naveeda & Wajahat, 2024). These findings suggest that students utilize the flexibility of online asynchronous courses to their benefit or convenience. To test this, the following hypotheses are proposed:

H_1 *There is a statistically significant difference between trends in day of the week for student access compared to a no day of the week effect for student access in an eight-week term.*

H_2 *There is a statistically significant difference between trends in time of the day for student access compared to a no time effect for student access in an eight-week term.*

Student Characteristics

Yao et al. (2022) found that students' self-awareness of their ability to use technology significantly influences their intention to engage with online learning. Interestingly, students in an asynchronous online course have a higher cognitive presence than students in a synchronous online course (Presley et al., 2023). Additionally, students prefer continuous assessment in learning modules compared to taking exams, and that continuous assessment assists with avoiding procrastination (Fynn & Mashile, 2022). Tan et al. (2022) found that activities promoting cooperative learning in an online environment can increase motivation to stay in the program for disadvantaged students.

Students in blended courses are better equipped to develop self-regulation in planning and monitoring their course activity behavior than students in online courses (Alharthi & Elsigini, 2022). However, this finding holds for male students but not for female students (Alharthi & Elsigini, 2022). Time management skills and active class participation predict academic success (Ting et al., 2022). And, students who can self-regulate perceived online learning as positive (Rivers, 2022).

Such student self-regulation may grow over time. According to Alzahrani (2023), students' cognitive engagement in online courses grows by week over four weeks as self-reported by the students. However, Alzahrani (2023) did not find a significant difference between male and female students in self-reported online course engagement. Self-reported use of online course materials was inconsistent with actual use, with most students over-reporting access to course materials (Akbulut et al., 2023). Interestingly, the authors found that female students were more consistent in their self-reporting than male students.

Upchurch et al. (2022) found that gender does not negatively impact access to formative assessments in fully online classes. Yet, according to Albaqawi (2022), female students were more persistent in accessing online learning than male students. Among Pakistani students, females were more likely to achieve higher GPAs in online courses than males (Iftikhar et al., 2023). Among both Polish and Ukrainian students, females spent less time online than males during the COVID-19 pandemic (Dymek et al., 2022). According to Idrizi et al. (2023), male and female students differ in final scores based on teaching modalities in STEM, with male students scoring better in online courses and female students scoring better in face-to-face courses.

Yet Chathuranga et al. (2023), found no difference in the perceived benefit of online learning between female and male students. Additionally, seniors have fewer barriers to formative assessments in online classes compared to first year students (Upchurch et al., 2022). To determine if differences can be observed in online course behavior between males and females, the following hypotheses are proposed:

H_3*. There is a statistically significant difference between males and females in total access hits by day of the week across all weeks for an eight-week term.*

H_4*. There is a statistically significant difference between trends in week of the semester for student access compared to a no week of the semester effect for student access in an eight-week term.*

H_5*. There is a statistically significant difference between males and females in total access hits across all weeks for an eight-week term.*

Learning analytics data from a learning management system was collected and analyzed to test these hypotheses.

METHODS

The study procedures were reviewed by the local Institutional Review Board in January 2023 (IRB FY22-23-158) and determined the study did not meet requirements for federally regulated research, was exempt from human subjects' protections, and required no further IRB oversight.

Subjects

For the first set of hypotheses (H_1 and H_2), the participants included 1,384 students in 38 distinct sections of 12 different Communication courses from 1000-level (n = 37 courses, N = 1,364 students) through 5000-level (n = 1 course, N = 20 students) and their instructors (n = 11) at a large research extensive university in the southwestern United States. The average class size was 26.29 students (*sd* = 7.41, minimum = 4, maximum = 79). Courses included sections taught Fall 2021 through Summer 2023. All sections of courses were taught utilizing an asynchronous online modality.

For the second set of hypotheses (H_3 through H_5), the participants were 147 students (62.59% female, 37.41% male) in 7 distinct sections of 7 different undergraduate courses from 2000-level through 4000-level and their instructors (n = 5, 3 females, 2 males) at a large research extensive university in the southwestern United States. The average class size was 26.29 students (*sd* = 7.41, minimum = 14, maximum = 35). Courses included sections taught Summer 2023. All sections of courses were taught utilizing an asynchronous online modality.

Procedures

All instructors within a department who taught online asynchronous courses were requested via email to participate in the study. Instructors participating in the study were asked to supply student access data from the Learning Management System (LMS) Blackboard. The LMS course reports requested were the "Overall Summary of User Activity" (H_1 through H_5) and the "Course Activity Overview" (H_3 through H_5). Specifically, faculty were asked to produce reports from the LMS which showed student access to the course by time and day for Fall and Spring Semesters, and for the eight-week summer quarter (H_3 through H_5) on a week-by-week basis, and submit the reports as Excel files for each course section. Once the data were collected, the data were checked for duplication as some students could have been registered in more than one section, then students were de-identified.

Data

The per course hourly and weekly access "hits" data from each section (H_1 and H_2) was parsed and transposed within Excel to create separate dataset tables for use in the analysis of overall trends of time and day access among all sections by instructor of asynchronous online courses for this study. Data for each section (H_3 through H_5) included the time-of-day access rounded to the nearest hour on a twenty-four-hour basis and day of the week access for each student in each section, bounded by 12:00am (midnight) U.S. Central Standard Time. The data may include, though is not identified by the LMS, multiple "hits" by a single student within a given time-frame due to logging out and logging back in within the time boundaries. Per student access "hits" and amount of time in spent online per week for each of the eight summer weeks was parsed from the individual reports provided by the instructors.

Data reveal that the average number of "hits" per course per week was 18687.57 (*sd* = 7368.60), and the average number of hours spent per course per week was 783.23 hours (*sd* = 358.86). Data also reveal across all sections that the hours between 9pm and 11pm were a peak time per week. The day of the week with the most "hits" across all sections was Sunday (N = 35809) with an average per week of 4476.13 "hits" (*sd* = 2040.52). Sunday also demonstrated the most hours spent online (N = 1703.50) with an average per week of 212.94 hours (*sd* = 98.94) across all sections. The total number of "hits" for all students across all eight weeks was (N = 130814, number of cells = 1464, or an average of 89.35 "hits" per cell, *sd* = 82.34).

Data also reveal that students spent a per week average of 3.74 hours (*sd* = 0.67) accessing online course materials, where female students spent a per week average of 3.44 hours (*sd* = 0.74) accessing online course materials, whereas male students spent a per week average of 4.27 hours (*sd* = 1.12), with students in multiple courses duplicated. Data also reveal that the average number of "hits" per student per week was 89.35 (*sd* = 13.15), with female students accessing the course an average of 83.14 (*sd* = 15.80) times and male students accessing the course an average of 100.10 (*sd* = 18.62) times. For hypothesis testing data were normalized across course sections by differences in class size, or by ratio of males to females per course section, then standardized using the Log(10) procedure in SAS.

Analysis

We consider the data in our study to be repeated measurements, such as those over seven days. Therefore, we exploit multivariate linear models to analyze the repeated measurements data and use the procedure GLM of SAS 9.3 to fit the model (SAS Institute, 2012). We also use the SAS procedure IML to arrange the data to more appropriately test the hypotheses (SAS Institute, 2012). We allow the variance-covariance matrix to be arbitrary but homogeneous across groups (genders) where the number of subjects within each group is at least equal to the number of repeated measurements acquired on each subject (Timm & Mieczkowski, 1997). To better illustrate the relationships between time and access, we tested hypotheses associated with the second dataset first (H_3 and H_4) comparing students by gender, followed by testing of the general trends in student access for time and day associated with the first dataset (H_1 and H_2), and then general differences between male and female students (H_5).

A profile is a graphical representation of a variable over 24 hours, 7 days, or 8 weeks (Khattree & Naik, 1999). A profile analysis is a collection of statistical hypotheses testing procedures which compare trends over time. The profile analysis examines parallelism of trend lines, group equality, and profile flatness.

RESULTS

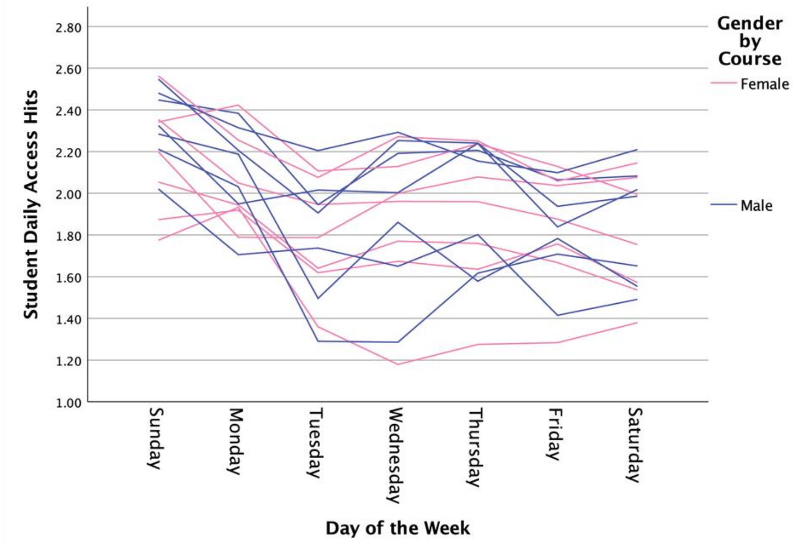
Hypothesis Testing H_3: Variable Normalized log10(TotalSDHits)

The study in this section aims to test whether there is any difference in access hits over seven days between males and females (dependent variable normalized log10(TotalSDHits); Total Daily Hits per Student). We want to test whether the mean profiles for the females and males are parallel? That is, we want to test the following hypothesis:

(1) H_0: Mean profiles of females and males in the students' hits in day of the week are parallel
vs. H_{3a}: Mean profiles of females and males in the students' hits in day of the week are not parallel

Since the class size varies from 4 to 76, we normalize the TotalSDHits by dividing it by the corresponding separate class sizes of male students and female students. We then take log of the normalized TotalSDHits. The null hypothesis H_0 in (1) represents the hypothesis of mean parallel profiles of females and males. The profile plot for females and males per course by day is given in Figure 1 and the mean profile for females and males across all courses per day is given in Figure 2.

FIGURE 1
PROFILES FOR DAY BY GENDER AND COURSE

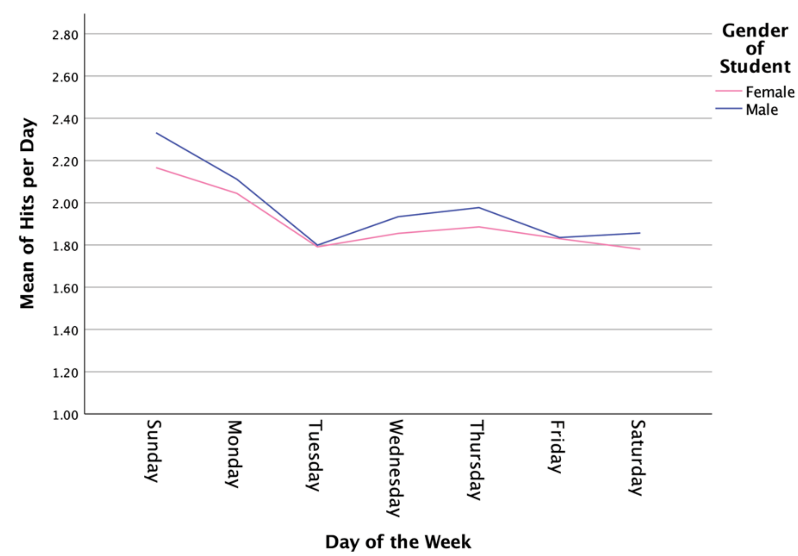


The test statistic value for H_0 in (1) is $F_{6,7} = 0.80$ with p-value = 0.5979. So, we fail to reject the null hypothesis of parallel mean profiles for females and males.

Given the parallel mean profiles for females and males, the next question to ask now is, whether the two mean profiles are identical? So, we want to test the following hypothesis:

(2) $\boldsymbol{H_0}$**:** Mean profiles of females and males in the students' hit in day of the week are coincidental
vs. $\boldsymbol{H_{3b}}$**:** Mean profiles of females and males in the students' hit in day of the week are not coincidental

FIGURE 2
MEAN PROFILES FOR DAY BY GENDER



The test statistic value for H0 in (2) is F1,12 = 0.26 with p-value = 0.6214. So, we fail to reject the null hypothesis of coincidental profiles for females and males. Now, the natural question is, whether the two profiles are horizontal? So, we want to test the following hypothesis:

(3) $\boldsymbol{H_0}$**:** Mean profiles of females and males in the students' hit in day of the week are horizontal
vs. $\boldsymbol{H_{3c}}$**:** Mean profiles of females and males in the students' hit in day of the week are not horizontal

The test statistic value for H_0 in (3) is $F_{6,7} = 17.04$ with p-value = 0.0007. So, the two profiles for females and males are not horizontal. That is, the log of normalized scores changes over seven days.

Hypothesis Testing H_4: Variable Normalized log10(TotalSWHits)

The study in this section aims to test whether there is any difference in access hits over seven weeks between males and females (dependent variable normalized log10(TotalSWHits); Total Weekly Hits per Student). We want to test whether the females' and males' weekly mean profiles are parallel over the first seven weeks. We exclude Week 8 from our analysis as classes only met for half a week. The weekly profile plot for all females and males is given in Figure 3 and the weekly mean profile for females and males separately is given in Figure 4. From these two figures we see the hits in week eight drop considerably. Furthermore, we have only seven courses in each female and male group. Number of subjects within each group should be at least equal to the number of repeated measurements acquired on each subject (Timm & Mieczkowski, 1997). So, we analyze the data only for first seven weeks.

The test statistic value for H_0 in a similar hypothesis like (1) is $F_{6,7} = 0.10$ with p-value = 0.9941. So, we fail to reject the null hypothesis of parallel weekly mean profiles for females and males.

Given the parallel mean profiles for females and males, we test whether the two weekly mean profiles are identical/coincidental. So, we test the hypothesis similar to a hypothesis (2). The test statistic value $F_{1,12} = 0.38$ with p-value = 0.5512. So, we fail to reject the null hypothesis of coincidental weekly mean profiles for females and males. We now test whether the two weekly mean profiles for first seven weeks are horizontal like the hypothesis (3). The test statistic value is $F_{6,7} = 3.28$ with p-value = 0.0728. So, the two weekly mean profiles for females and males are horizontal given a significance level at $\alpha = 0.05$. That is, the log of normalized scores for both females and males do not change over seven weeks.

FIGURE 3
PROFILES FOR WEEK BY GENDER AND COURSE

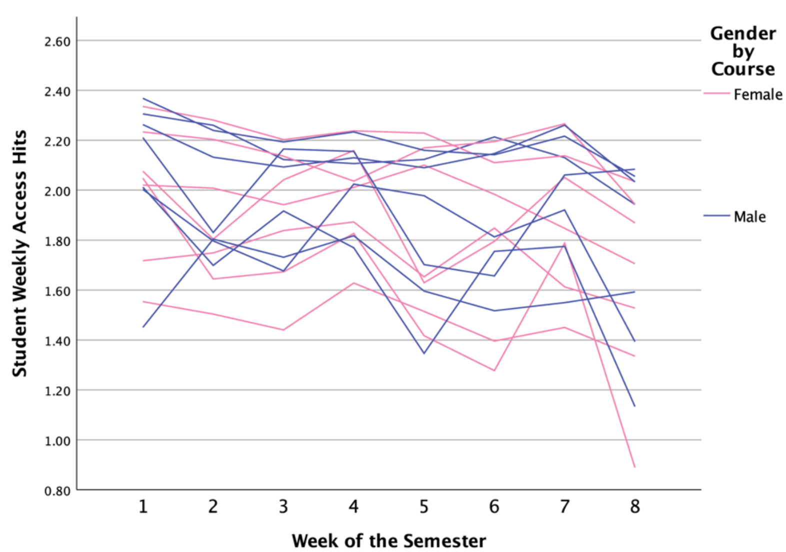
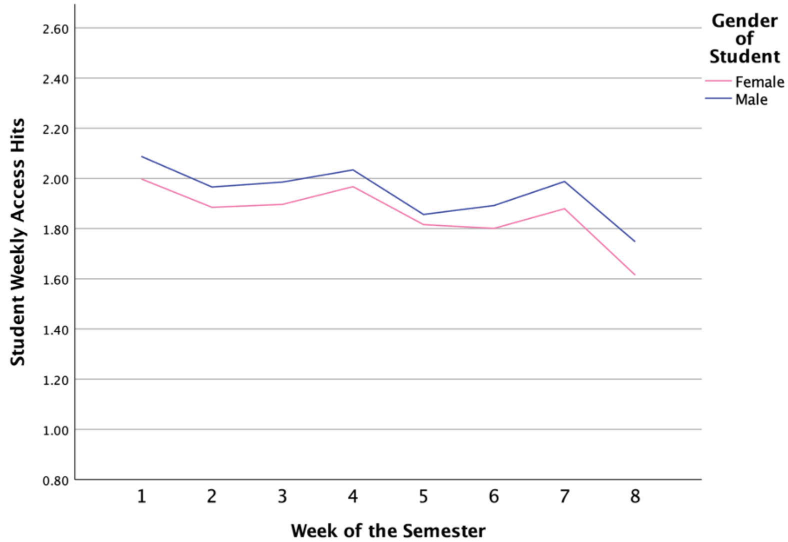


FIGURE 4
MEAN PROFILES FOR WEEK BY GENDER



Hypothesis Testing H_1: Variable Normalized log10(TotalDHits)

We also wanted to test whether there were trends by day of the week over all seven days (H_1). The class size varies across 38 course sections (see Table 1) with class size varying between 4 and 76 students, excepting the Master's level course which only had one section of 20 students.

Therefore, we normalized the TotalDHits (Total Daily Hits by Course) by dividing it by the corresponding class size. We then took the log of the normalized TotalDHits for the dependent variable and tested the following hypothesis:

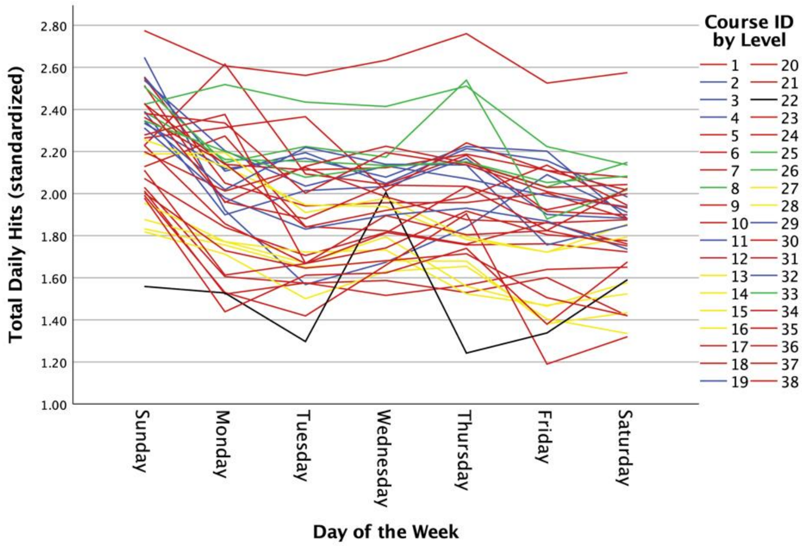
(4) $\boldsymbol{H_0}$**:** There is no overall difference in students' access hits among days of the week.
vs. $\boldsymbol{H_1}$**:** There are differences in students' access hits among days of the week.

TABLE 1
NUMBER OF COURSE SECTIONS AND STUDENTS BY COURSE LEVEL

Course Level	Description	n of Sections (CourseID)	N of Students	*M* (per Class)
Level 1 (L1)	Freshman	6	447	74.50
Level 2 (L2)	Sophomore	4	83	20.75
Level 3 (L3)	Junior	20	637	31.85
Level 4 (L4)	Senior	7	197	28.14
Level 5 (L5)	Masters	1	20	

The null hypothesis H_0 in (4) represents the hypothesis of a horizontal profile. In other words, there is no overall difference in the students' access hits during any day of the week considering all the five course levels together. The profile plot for each class is given in Figure 5 below. In this figure, Gold represents Level 1 (Freshmen), Green represents Level 2 (Sophomores), Red represents Level 3 (Juniors), Blue represents Level 4 (Seniors), and Black represents Level 5 (Masters).

FIGURE 5
PROFILES BY DAY FOR ALL COURSES INDEPENDENTLY



If we consider that the top Red profile (CourseID 1, which had a class size of six students) may be an outlier, overall we see the hits in Level 2 (L2, Green profiles) as the upper bound and Level 1 (L1, Gold profiles) as the lower bound. Level 5 (L5, Black profile) has only one class, so no statistical analysis can be conducted. The mean profile for daily access hits for all courses combined is given in Figure 6.

The test statistic value for H_0 in (4) is $F_{6,32} = 54.70$ with p-value $< .0001$. So, we conclude that there are differences in students' access hits among the days of the week. This conclusion encourages us to do some post-hoc analysis. The five mean profiles for five course levels by Day are given in Figure 7. We see five mean profiles for five levels are different; thus, we want to test whether pairwise differences are significant; e.g., L1 and L2, L1 and L3, L1 and L4, L2 and L3, L2 and L4, and L3 and L4.

FIGURE 6
MEAN PROFILE BY DAY ACROSS ALL COURSES COMBINED

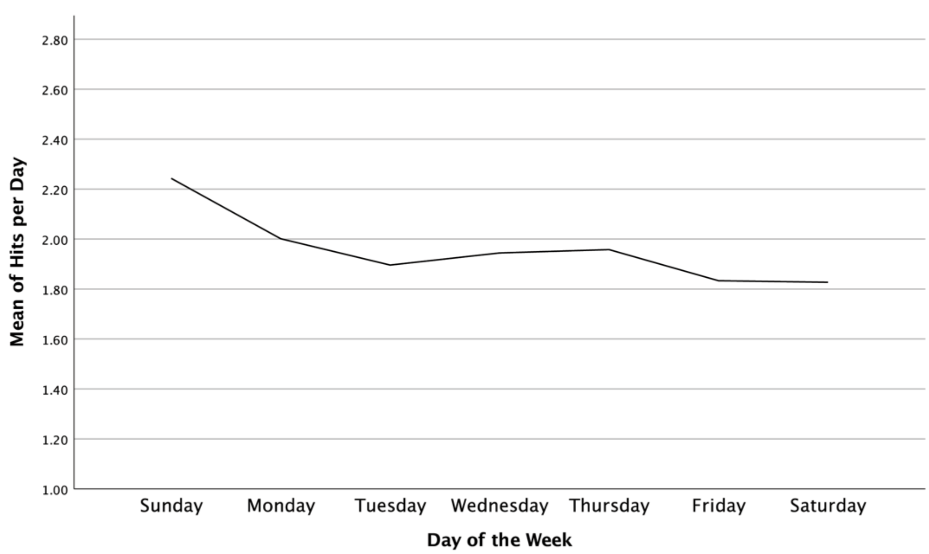
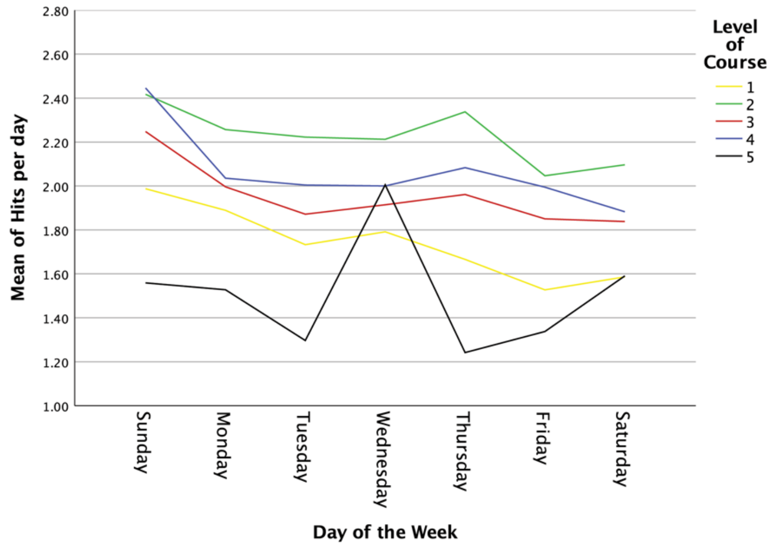


FIGURE 7
MEAN PROFILE BY DAY BY COURSE LEVEL



From Figure 7 we see that L1 (Gold) and L2 (Green) are not parallel and there are differences in the hits. However, we cannot test the two whole profiles simultaneously as we have only six classes in L1 and four classes in L2. We can only test a segment of four days: e.g., first four days (Sunday-Wednesday) or the last four days (Wednesday -Saturday). For the first four days, i.e., (Sunday-Wednesday) we get $F_{3,6}$ = 1.67 with *p*-value 0.2713. So, we fail to reject the null hypothesis of parallel mean profiles for L1 and L2. Next, we test whether these levels are coincidental. We get $F_{1,8}$ = 18.14 with *p*-value 0.0028; so, the profiles for L1 and L2 are not coincidental: Level 2 classes have definitely more hits than Level 1 in the first segment of the week.

We do the same analysis for the week's last four days (Wednesday-Saturday). We get $F_{3,6}$ = 8.21 with *p*-value 0.0152. So, we reject the null hypothesis of parallel mean profiles for L1 and L2 students for the last four days of the week. The test statistic values and the corresponding *p*-values for both the segments are given in Table 2. For coincidental test of the two mean profiles for L1 and L2 we get $F_{1,8}$ = 40.64 with *p*-value 0.0002. From all these *p*-values we conclude that Level 2 classes definitely have much more hits than Level 1 classes in the last segment of a week.

From Figure 7 we see that L1 (Gold) and L3 (Red) are not parallel and there are differences in the hits, especially at the end of the week. However, we cannot test the two whole profiles simultaneously as we have only six classes in L1 and twenty classes in L3. We can only test a segment of six days: e.g., first six days (Sunday-Friday) or the last six days (Monday-Saturday). The test statistic values and the corresponding *p*-values for both segments are given in Table 2. We reject the null hypothesis of parallel mean profiles for L1 and L3 for both segments. We then see the two profiles are coincidental given a significance criterion of $\alpha = 0.05$; i.e., differences in the hits in the two levels L1 and L3 are not statistically significant.

From Figure 7 we also see that L1 (Gold) and L4 (Blue) are not parallel. As we have only six classes in L1 and seven in L4, we can only test the first six days of the week (Sunday-Friday) or the last six days (Monday-Saturday). For parallel mean profiles test, the test statistic values and the corresponding *p*-values for both the segments are given in Table 2. We reject the null hypothesis of parallel mean profiles for L1 and L4 for the first segment and fail to reject for the last segment. We then see the two profiles are not coincidental. Thus, we see Level 4 classes have much more hits than Level 1 classes in both the segments of a week.

TABLE 2
POST-HOC ANALYSIS FOR HYPOTHESIS H_1

Pairwise test	Sample size	Parallel F-value	p-value	Coincidental F-value	p-value	Inference (α = 0.05)
L1 and L2	(6 and 4)	(Sun-Wed)				L2 has more hits than L1
		$F_{3,6}$ = 1.67 (Wed-Sat)	0.2713	$F_{1,8}$ = 18.14	0.0028	L2 has more hits than L1
		$F_{3,6}$ = 8.21	0.0152	$F_{1,8}$ = 40.64	0.0002	L1 and L3 are not significantly different
L1 and L3	(6 and 20)	(Sun-Fri)				
		$F_{5,20}$ = 4.25 (Mon-Sat)	0.0086	$F_{1,24}$ = 3.42	0.0767	L1 and L3 are not significantly different
		$F_{5,20}$ = 4.27	0.0084	$F_{1,24}$ = 3.14	0.0890	L4 has more hits than L1
L1 and L4	(6 and 7)	(Sun-Fri)				
		$F_{5,7}$ = 4.67 (Mon-Sat)	0.0341	$F_{1,11}$ = 20.94	0.0008	L4 has more hits than L1
		$F_{5,7}$ = 3.47	0.0676	$F_{1,11}$ = 16.28	0.0020	L2 and L3 are not significantly different
L2 and L3	(4 and 20)	(Sun-Wed)				
		$F_{3,20}$ = 1.43 (Wed-Sat)	0.2637	$F_{1,22}$ = 4.05	0.0567	L2 has more hits than L3
		$F_{3,20}$ = 0.77	0.5233	$F_{1,22}$ = 4.31	0.0498	L2 and L4 are not significantly different
L2 and L4	(4 and 7)	(Sun-Wed)				
		$F_{3,7}$ = 1.45 (Wed-Sat)	0.3067	$F_{1,9}$ = 4.89	0.0544	L2 has more hits than L4
		$F_{3,7}$ = 1.36	0.3319	$F_{1,9}$ = 8.94	0.0152	
L3 and L4	(20 and 7)	$F_{6,20}$ = 1.97	0.1176	$F_{1,25}$ = 1.17	0.2890	L3 and L4 are not significantly different

From Figure 7 we also see that L2 (Green) and L3 (Red) are parallel. Here also we cannot test the whole profile at one time. L2 has four classes and L3 has twenty classes. So, we can only test a segment of four days: e.g., first four days (Sunday-Wednesday) or the last four days (Wednesday-Saturday). For parallel mean profiles test, the test statistic values and the corresponding p-values for both the segments are given in Table 2. We fail to reject the null hypothesis of parallel mean profiles for L2 and L3 for both the segments. For coincidental mean profile test, the test statistic values and the corresponding p-values for both segments are also given in Table 2. We see the first segment is not statistically significant; however, the second one is (marginally). This means Level 2 classes have much more hits than Level 3 classes in the last segment of a week.

From Figure 7 we also see that L2 (Green) and L4 (Blue) are parallel. Here also we cannot test the whole profile at one time. L2 has four classes and L4 has seven classes. So, we can only test a segment of four days: e.g., first four days (Sunday-Wednesday) or the last four days (Wednesday-Saturday). For parallel mean profiles test, the test statistic values and the corresponding p-values for both segments are given in Table 2. We fail to reject the null hypothesis of parallel mean profiles for L2 and L4 for both segments. For coincidental mean profile test, the test statistic values and the corresponding p-values for both segments are also given in Table 2. We see the first segment is not statistically significant, however the second one is. This means Level 2 classes have much more hits than Level 4 classes in the last segment of a week.

Finally, we test whether the mean profiles for L3 (Red) and L4 (Blue) are parallel and then coincidental. Since the number of classes in both the levels are ≥ 7, we can test the whole profile at one time. The test statistic value and the corresponding *p*-value are given in Table 2. We see the mean profiles for Level 3 and Level 4 are identical. So, activities of these two levels of classes are very similar.

Hypothesis Testing H_2: Variable Normalized log10(TotalHHits)

The purpose of the study in this section is to test whether there is any difference in the log10(TotalHHits) (Total Hourly Hits per Course) scores over twenty-four hours. Since the class size varies across CourseID, we normalized the TotalHHits by dividing it by the corresponding class size. We then took the log of the normalized TotalHHits. In order to determine whether student access hits change over time (H_2), we tested the following hypothesis:

(5) $\boldsymbol{H_0}$**:** There is no overall difference in students' access hits among hours of the day.
vs. $\boldsymbol{H_2}$**:** There are differences in students' access hits among hours of the day.

The null hypothesis H_0 in (5) represents the hypothesis of a horizontal profile. So, we test the hypothesis similar to a hypothesis (4). In other words, there is no overall difference in the students' hits during any hour of the day taking into account all the five course levels together. The mean profile for all course taken together is represented in Figure 8 below.

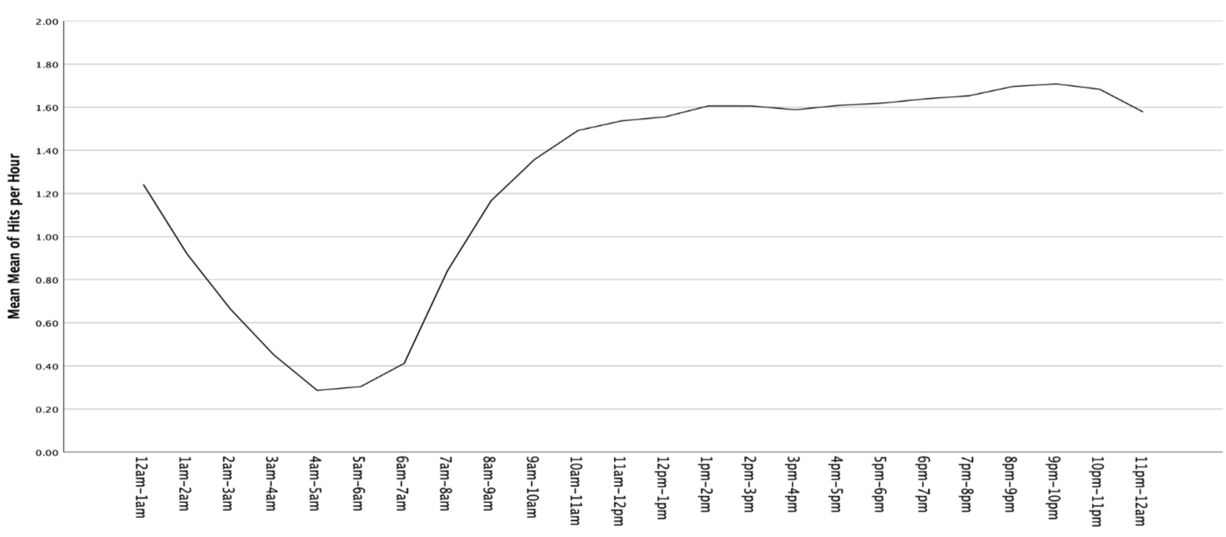
The test statistic value for H_0 in is $F_{23,14} = 31.77$ with *p*-value < .0001. Therefore, we conclude that there are differences in students' access hits among hours of the day.

Hypothesis Testing H_5: Variable Normalized log10(TotalSHits)

The purpose of the study in this section is to test whether there is any difference in the access hits between males and females over the course of a semester (dependent variable normalized log10(TotalSHits); Total Student Hits per Course).

Test results indicated no significant difference between female students (N = 92, $M = 2.73$, $sd = .27$) and male students (N = 55, $M = 2.82$, $sd = .29$), $t_{145} = -1.81$, *p*-value = 0.072 (two-sided), Cohen's d = -.309.

FIGURE 8
MEAN PROFILE FOR HOUR ACROSS ALL COURSES



DISCUSSION AND CONCLUSION

Profiles of student access hits in online asynchronous courses demonstrate a non-linear pattern by week, day and hour, with activity spread across all possible opportunities for course engagement. Peaks by day occur primarily on Sundays, with a general downward trend over the next six days. These daily trends held for undergraduate courses regardless of level, though they did not appear to hold for a Master's level course. The daily trends also held for both female and male students.

Similarly looking trends held for a week of the semester for eight-week courses, with a general downward trend from the beginning of the semester until the student access hits picked up again in the seventh week. Although male and female students by course level appeared to differ in their course access, our analysis demonstrated no significant differences between male and female students. General trends by gender were parallel for both day of the week and week of the semester.

Although we only investigated general hourly trends for the 38 courses in our dataset, our preliminary analysis also demonstrated a non-linear trend line for hourly access with a substantial drop in activity between the hours of 1am and 5am, an increase of activity in the morning hours of 6am to 11am, and a fairly flat plateau of activity between noon and 8pm with a slight peak between 9pm and 10pm.

These trends are interesting considering they occur with an online asynchronous course that allows access at any time convenient to the student. It also shows that most student activity occurs outside the normal operating hours of traditional face-to-face courses. According to Alyahya and Bhatti (2022), teachers' ability to effectively use an LMS to deliver online course content influences the sustainability of the educational enterprise of students.

Most telling of our findings was the lack of support for the hypothesis that male and female students should diverge in their online activity. Previous research cited in the literature review clearly recommended such difference to be found. Perhaps the expectation was based on research that took a different data-gathering approach. To be sure, many of the cited studies used self-report. However, the convergence of observed behaviors among male and female students in the current study may be a function of a conditioned response to the trauma of a global pandemic where students and faculty alike were forced to undertake remote online education or possibly could be due to cultural or economic exigencies which are dealt with similarly despite past expectations of gender. Regardless, the nature of the data here are not due to self-reported attitudes which these cultural expectations might bias. Rather the data are derived from real-time action recorded by a disinterested learning management system.

These findings may help practitioners in higher education consider course design in reference to constant access. It seems that students may, for reasons associated with other outside obligations such as work or family, or both, utilize the convenience of online asynchronous education to management their time much differently than might be available to them in tradition face-to-face education. In may also be that these observed trends could be due to other cultural factors not measured here.

For these reasons, among others, this study is not without limitations. To be sure, the learning management system collected access data of students, but was not particularly designed to collect data in the organized fashion designed for research purposes. The study authors were required to use means to turn the data, such as converting access dates to particular days of the week for analysis. Additionally, the LMS did not collect other demographic information typically collected in quasi-experimental studies, such as ethnicity, income, or age, which may have given insight into these observed trends in access.

Despite these limitations, this study points to areas of future research, including the amount of time spent accessing online content and whether such access patterns can be associated with learning outcomes. Regardless, educators should consider the context in which modern students live when designing their courses.

ACKNOWLEDGEMENTS

I wish to acknowledge the faculty in the Department of Communication at the University of Texas at San Antonio who provided data from their classes for this study.

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