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Effects of the COVID-19 pandemic on the online learning behaviors of university students in Taiwan

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Abstract

Prior to the coronavirus disease 2019 (COVID-19) pandemic, due to the rarity of pandemics in recent centuries, suitable conditions did not exist in educational institutions for the implementation of asynchronous distance teaching. No empirical studies have been conducted on whether the considerable environmental changes caused by COVID-19 have affected students' online learning behaviors. Therefore, this study collected information on students' online learning behaviors during the COVID-19 pandemic and other periods to examine whether pandemic-caused environmental changes affected students' online learning behaviors. This study focuses on the 60-day transmission after the beginning of the second semester of the 2019 academic year. The data source was from a comparative assessment between the pandemic group (331 students) and the control group (101 students). The Spearman Rank Correlation Test and the Wilcoxon signed-rank test were used as our statistical methods. This paper presents preliminary results on how COVID-19 has affected students' online learning behaviors and proposes asynchronous online learning as a method for maintaining university students' learning during the COVID-19 pandemic.

Keywords Learning analytics · Data mining · e-Learning · Asynchronous online learning · COVID-19 pandemic

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1 Introduction

Coronavirus disease 2019 (COVID-19) emerged in December 2019 (Liu et al., 2020) and was declared a global public health emergency on March 11, 2020, by the World Health Organization (WHO) (Cucinotta & Vanelli, 2020). Since then, it has rapidly progressed into a pandemic. Unconstrained by borders, the virus spread quickly, prompting countries worldwide to adopt measures such as closing their borders, controlling entry and exit points, and disease tracking to curtail the disease outbreak. These measures not only have a high economic cost (Al-Awadhi et al., 2020; Laing, 2020) but also impose stress on public education systems.

During the COVID-19 pandemic, 194 countries and regions temporarily closed their educational institutions, affecting over 1.5 billion students worldwide (The United Nations Educational, Scientific and Cultural Organization [UNESCO], 2020). Fortunately, mobile devices that can connect to the Internet have allowed students to continue learning in digital environments. Transcending the spatial limitations of conventional classrooms, digital learning allows for students to follow the learning content prescribed by educational institutions and teachers using their preferred learning methods and at their convenient time and location (Crompton, 2013; Martin & Ertzberger, 2013). Educational institutions worldwide have attempted to apply educational technology for providing synchronous or asynchronous online learning. These types of distance learning have become the optimal solution for reducing the effect of the COVID-19 pandemic on student learning and also provides flexibility to teachers. However, the use of such teaching methods may give rise to various problems, such as data security issues in teaching streaming platforms (Ministry of Education [MOE], 2020a) and problems related to decreased exercise levels and prolonged sitting among students (Xiang et al., 2020). Researchers have also warned that the pandemic would exacerbate mental stress (Flett & Zangeneh, 2020). In Israel, a survey of 313 professors confirmed that mental stress during the COVID-19 pandemic has been higher than that before the pandemic. However, no study has empirically examined whether students of online distance learning have changed their learning behaviors due to the COVID-19 pandemic.

Due to the COVID-19 pandemic, students must maintain social distancing and learn at home. However, they can still receive daily updates about the pandemic through both new and traditional media. Such updates can cause intangible stress to students to maintain their studies. In a US survey of a university with approximately 15,000 students in a midwestern city, 78% of the 992 respondents answered that they received most of their information about COVID-19 from the Internet and social media (Chesser et al., 2020). Chesser et al. (2020) stated that in addition to pursuing their studies at home, students use the Internet to receive real-time information on the COVID-19 pandemic across the world, which may lead to changes in their online learning behaviors compared with that during prepandemic times. Therefore, the goal of this study was to investigate whether the COVID-19 pandemic affected the online learning behaviors of Taiwanese university students receiving asynchronous online distance learning.

2 Literature review

2.1 Education in Taiwan under the COVID-19 pandemic

2.1.1 Response measures during the pandemic

The first confirmed case of COVID-19 in Taiwan was reported on January 21, 2020, 10 days before the WHO declared COVID-19 a global public health emergency. On February 3, 2020, Taiwan's MOE announced that universities and colleges would remain closed until February 25, 2020, after which each institute would set its own academic calendar. On February 6, a mask rationing program was implemented, and 2 weeks later (February 20), the MOE announced standards for the suspension of classes that were stricter than the enterovirus standards. If a teacher or student receives a confirmed diagnosis, all their classes would be suspended, and two confirmed diagnoses would result in a school- or campus-wide suspension of classes, with make-up classes being held online. Each suspension would last for 14 days. On February 27, the Taiwan Central Epidemic Command Center was upgraded to a Level One alert. Within the next two weeks, on March 10, the Taiwanese government announced the *Special Act for Prevention, Relief and Revitalization Measures for Severe Pneumonia with Novel Pathogens*. On March 13, the MOE asked universities and colleges to assess carefully the pandemic situation in each country and the risk of infection by air travel and to reduce or suspend overseas travel by teachers and students. However, on March 16, the first COVID-19 case involving a Taiwanese high school student being infected when traveling overseas was reported. The next day, the MOE announced the students in high school and lower grades should avoid unnecessary and non-urgent overseas travel. On March 19, the MOE announced the suspension of high school classes, with confirmed cases of infection between students. By the end of March, following a confirmed case of COVID-19 in a certain class, a university voluntarily moved all their classes online. After a second case was confirmed in the same class 9 days later, the aforementioned university canceled the scheduled interviews and written exams and adopted application reviews for their second round of admittance. On April 21, the standing committee of the Joint Board of College Recruitment Commission announced that students unable to participate in their advanced subjects tests due to the COVID-19 pandemic may be administered make-up tests.

Since April 13, 2020, no new local cases of infection have emerged in Taiwan. After 8 consecutive weeks without any local cases, on June 7, the COVID-19 prevention guidelines were considerably loosened. According to the website of the Ministry of Health and Welfare (MOHW) that outlines crucial policies for combating COVID-19 (https://covid19.mohw.gov.tw/ch/mp-205.html), as of June 18, 2020, Taiwan has had 445 confirmed cases (and seven deaths). Of these cases, 352 involve overseas infections and 55 involve local infections. Moreover, 36 cases have been reported among navy crew aboard the Panshi Fast Combat Support Ship. During the pandemic, in addition to implementing temperature checks

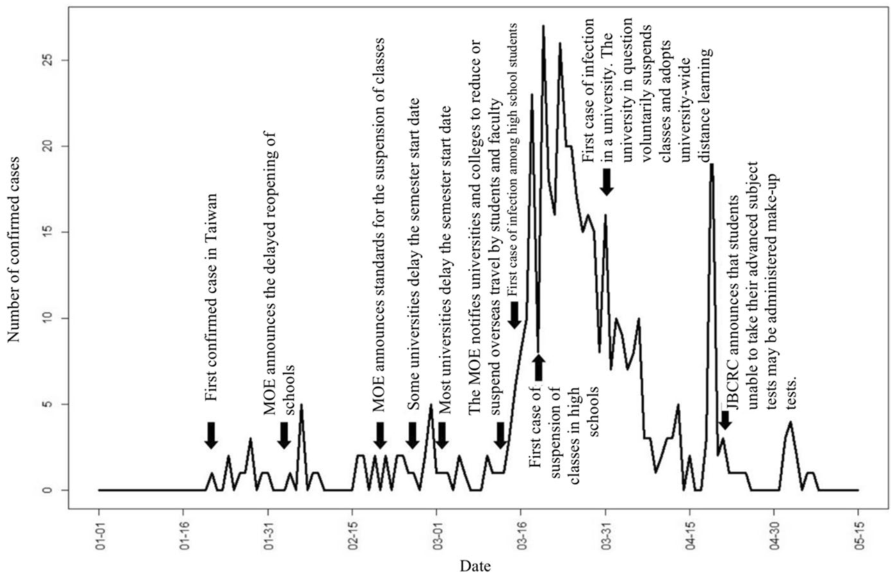

Fig. 1 Major education events in Taiwan during the COVID-19 pandemic in 2020

and contact tracing measures on campus personnel, universities and colleges have proactively promoted institution-wide, large-scale online teaching drills or distance teaching response measures. Figure 1 presents the key timepoints of major education events in Taiwan during the COVID-19 pandemic.

Figure 1 indicates that although universities complied with the directions of the MOE and delayed the beginning of the second academic semester of 2019, the first half of the semester still occurred during the peak of the pandemic in Taiwan. Many school campuses also implemented numerous pandemic measures, such as distance learning, during this time.

2.1.2 Distance learning during the pandemic

In compliance with the Central Epidemic Command Center's regulations on social distancing, Taiwanese educational institutions have made changes to the teaching of large classes and in-person instructions in classrooms with poor ventilation. These changes have involved instructors moving physical classrooms to virtual classrooms on digital learning management systems (LMSs) and offering synchronous or asynchronous teaching through remote classes. However, synchronous teaching has been criticized as being having instructor-centric designs that emphasize teachers over students (Murphy et al., 2011). Consequently, the small private online courses and massive open online courses (MOOCs) originally offered by universities as forms of distance learning became the favored choices of many students who were in quarantine or unable to enter Taiwan during the COVID-19 pandemic. For example, National Chiao Tung University in Hsinchu created a summer online college that does not involve any form of physical learning (https://www.ewant.org/). This university has conducted classes on existing MOOCs from 12 colleges and universities aimed at enrolled undergraduate institutions and high school seniors in Taiwan. The classes provided by this online college are recognized for school credits by 42 universities and colleges and are free of charge for economically disadvantaged students.

To combat the COVID-19 pandemic without suspending classes, the MOE has set up a nationwide online teaching platform that spans all academic systems, including higher education (https://learning.cloud.edu.tw/onlinelearning/). This platform also provides an inventory of digital learning classes and resources across all platforms that can be used by all schools (MOE, 2020b). For economically disadvantaged students or students whose schools were suspended and are now taking classes online at home, the aforementioned platform coordinates with telecommunication providers to provide discount Internet packages, such as free 4G SIM cards and other student discounts.

2.2 Environmental factors influencing online learning behaviors

During the COVID-19 pandemic, in addition to facing challenges related to their basic biological and safety needs, students are met with many changes to the overall social climate, campus safety, and the general environment based on the guiding principle of uninterrupted learning. Environmental psychology explores how people and environments influence each other. This field examines not only how individuals change the environment but also how the behaviors and experiences of individuals are affected by the environment and how changes are manifested (Hsu & Yang, 2005). The changes caused in the general environment by the COVID-19 pandemic is a topic worthy of research, especially with regard to whether the pandemic affected the learning behaviors of students.

Stimulation theories in environmental psychology indicate that environmental stimuli comprise the elements of amount and significance. The former includes the amount of time, the frequency, and the amount of sources, whereas the latter comprises personal perceptions of social interactions, the influencing factors of work performance, and health problems resulting from people's responses to stimuli (Hsu & Yang, 2005). Due to the recent emergence of environmental psychology as well as experimental and research ethics, few empirical studies have been conducted on the influence of environments on behaviors. Moreover, studies have rarely investigated students' perceptions of educational institution buildings or environment spaces (Ho & Chang, 2011; Shieh & Wang, 2009) or explored the effects of learning environments on learners' mood from a positive psychological perspective (Pekrun, 1992, 2000; Wu et al., 2011).

Some psychologists have investigated how COVID-19 has affected people's behaviors in terms of threat perception, social backgrounds, the adjustment of personal and collective interests, stress, and coping (Bavel et al., 2020). These psychologists have concluded that the COVID-19 pandemic has affected people psychologically (Holmes et al., 2020; Rajkumar, 2020; Zhang et al., 2020). A survey of 106 men and 157 women indicated that 52.1% of the 263 participants experienced fear and worry because of the COVID-19 pandemic (Zhang & Ma, 2020). The University of Valladolid in Spain analyzed 2530 online responses to the Depression Anxiety Stress Scale-21 and found that 50.42% of the respondents expressed medium to severe levels of anxiety, depression, and stress due to the pandemic. Other researchers (Harper et al., 2020; Pakpour & Griffiths, 2020) have proposed that fear may be the driving force to human behavioral changes during the pandemic, especially among people with high perceptions of self-efficacy or in situations with perceivable benefits (Witte & Allen, 2000).

Because humans have not encountered many worldwide pandemics in recent history, few empirical studies have examined the effects of public health events on student learning. However, some scholars have confirmed that students perceive environmental changes that result from a pandemic and therefore exhibit changes in their learning or behaviors. For example, an investigation of 624 clinical medical students (both undergraduate and graduate) indicated that compared with nonresident students, resident students were more likely to perceive themselves being infected with COVID-19 and therefore had greater desire to obtain knowledge about the disease and experienced higher difficulty in sleeping during the pandemic (Liu et al., 2020). In addition, 96 students responded to an online survey in Ukraine on their emotional journey and behaviors while isolating during the COVID-19 pandemic. The results indicated that 36% of the respondents held negative attitudes toward the future, and approximately half of the respondents (48%) were completely unwilling to leave their home (Haletska et al., 2020).

2.3 Online learning behaviors

According to the theory of behavioral psychology, feedback on students' behavior characteristics and psychodynamics can be obtained by analyzing their behavioral data (Liang et al., 2017). LMSs can record a student's online operational behaviors, which are stored as part of a student profile. Instructors can then mine the data in the student profile to observe his or her learning behaviors. The students' operational behaviors while engaging in online learning are considered their learning behaviors (Liu & Feng, 2011) and can represent either the explorative learning behavior or learning engagement patterns. Different LMSs have their constraints in data collection, and online operational behaviors are diverse. Researchers can retrieve the records of diverse online operational behaviors to deduce information not directly shown in the raw data. When a student clicks on a specific function in the LMS, the history and time of this action will be logged in the database as part of the student profile. Such online operational behaviors, once properly interpreted, can reflect the students' online learning behaviors. Online learning behaviors are mostly calculated on the basis of frequency and time (Shang et al., 2020), including the total frequency of which a course was accessed (Asarta & Schmidt, 2013), the total frequency and total duration of which a resource was accessed (Morris et al., 2005), the total frequency or duration of which a teaching video was accessed (Lin et al., 2017;

Lust et al., 2013; Ziebarth & Hoppe, 2014), the time of which a test was taken (Li & Baker, 2018), and the total number of posts created in online discussion (Sunar et al., 2018). After researchers collect these online learning behaviors, data cleaning must be performed to prevent bias caused by abnormal values (Agrawal et al., 2014), and the adequacy of the behavioral data collection must be verified (Dumais et al., 2014). This is to prevent the effect of deliberate online operational behaviors elicited by competition among users. For example, Fetterly et al. (2004) discovered that people deliberately engage in operational behaviors such as repeated clicks to improve their ranking. This indicates that researchers must carefully collect data on online learning behaviors and exclude items for which students are likely to be affected by the score, that is, items from which students can earn higher scores by clicking more frequently or investing additional time.

In summary, although studies have indicated that people are psychologically and behaviorally affected by pandemics, the effects of pandemics on students' online learning behaviors have not been investigated. The COVID-19 pandemic continues to affect Taiwan and many other parts of the world; therefore, studies on its influence on students' online learning have become a focus for researchers. This study investigated the online learning behaviors of 331 students from an educational institute in Taiwan who enrolled in asynchronous remote learning classes during the second semester of the 2019 academic year. Learning analysis was performed on the students' online learning experiences. These experiences were analyzed in terms of the daily pandemic and general environmental development within Taiwan and compared with the online learning experiences of 103 students who had taken asynchronous remote learning classes on the same LMS platform as the aforementioned 331 students during the second semester of the 2018 academic year. In this study, students' online video viewing behavior was the only behavior not included in the teacher's grade calculations. As such, the online learning behaviors referred to in this study are the behaviors of students viewing online videos.

The two research questions investigated in this study were as follows:

1. Did a correlation exist between the development of the COVID-19 pandemic and the online learning behaviors of the university students?
2. Did differences exist in the online learning behaviors of two groups of university students, namely the COVID-19 group and control group?

3 Research method and process

3.1 Research design and participants

3.1.1 Research design

This study aimed to investigate the effects of the environmental factors of COVID-19 on students' online learning behaviors. Because COVID-19 is a global pandemic and its development could not be predicted, all the students in Taiwan experienced the same environmental factors. This limitation prevented a randomized control test from being conducted. However, the effect of general environmental factors affected by the COVID-19 pandemic on university students' online learning behaviors remained the focus of this study.

After considering general environmental restrictions that would hinder the experiment and ethical requirements, the researchers used learning analysis to investigate the university students' online learning behaviors. After defining the behaviors to be observed in this study, the researchers performed time sampling in a systematic manner. Time sample records for similar periods and different environmental backgrounds (pandemic and nonpandemic times) were compared.

3.1.2 Participants

The time sampling data of two student groups, which comprised a total of 434 students, were investigated. The aforementioned two groups comprised students enrolled in asynchronous online learning courses offered by a certain university. One group comprised 103 students enrolled in the second semester of the 2018 academic year (nonpandemic time). The other group comprised 331 students enrolled in the second semester of the 2019 academic year (pandemic time). The students of the two groups had enrollment backgrounds and had completed class registration before the COVID-19 outbreak. Before registering for the class, the students knew that the course involved asynchronous online learning. The main difference between the two groups was that the COVID-19 group ($n = 331$) took the course during the height of the pandemic.

The students who took the course during the pandemic registered for the course at the end of the previous semester prior to the disease outbreak. The course selection was completed through the institution's preregistration system. Prior to the changes in the general environment, teachers and students had already finalized their class schedule for asynchronous online learning. This situation is different from those of other institutions, who were compelled to move their teaching systems online or change their teaching models due to the general environmental changes caused by COVID-19.

The researchers believe that compared with impromptu migrations from physical classrooms to remote learning due to the environmental changes caused by the COVID-19 pandemic, the online learning behaviors of the two student groups considered in this study would better highlight the effects of general environmental factors on student online learning. By examining the learning behaviors of these two groups, the effects that may arise from insufficient preparation for online teaching by instructors, insufficient preparation for online learning by students, or differences between enrollment motivations and needs can be eliminated or controlled.

3.2 Virtual classroom of the LMS, online teaching designs, and online learning behaviors

3.2.1 Virtual classroom of the LMS

Data on the online learning of the 434 students considered in this study were obtained from the online LMS platform of the selected institute. On the platform, each course has an individual virtual classroom, which may only be accessed by the teacher, assistant teacher, and enrolled students through their personal accounts and passwords. For mobile learning and cross-device learning, the virtual classroom supports desktops, tablets, and mobile devices; students may engage in online learning through desktop browsers or mobile apps.

3.2.2 Online teaching designs

Although the online learning data of the 434 students were obtained from three courses, these courses adopted similar asynchronous teaching designs. The following four online teaching designs were offered by the selected institute in accordance with the MOE's digital course certification: (1) asynchronous online video materials, (2) asynchronous online topical discussions, (3) asynchronous online self-evaluations (including ability tests), and (4) asynchronous online assignments and peer evaluation activities. Because the courses involved asynchronous remote classes, students could log on and take classes at their preferred times. However, the courses were divided into two independent learning schedules—the first 9 weeks from the start of the semester until the midterm exams and the next nine weeks from the midterm exams to the final exams. The students were required to complete certain online learning activities within the specified learning schedule. The four teaching designs were categorized as teaching or evaluation activities. Asynchronous online video materials were the only teaching activities used by the teachers to convey the course content. The remaining designs were formative and summary evaluations.

The only activity not graded was the students' browsing of asynchronous online video materials. All the other activities were graded.

3.2.3 Online learning behaviors

The researchers collected the logs of 434 students' learning journeys, which were documented at the back-end of the LMS virtual classroom platform, and analyzed the students' online learning behaviors. The goal of this study was to observe whether changes in the external general environmental changes affected the students' learning behaviors in the asynchronous online learning courses, which involved considerable self-learning. The number of hours spent by the students in watching asynchronous online videos was defined as the indicator of online learning behavior.

3.3 Data collection and preprocessing

To analyze the students' online learning behaviors accurately and to avoid possible social desirability biases resulting from memory effects. The main data sources were the online databases of the students' online learning journeys. Because data mining allows researchers to extract beneficial rules (Tseng et al., 2005), this method was used in the present study for learning analysis.

The data used in this study were acquired from internal and external databases. The internal data were mainly obtained from student online learning databases stored on the selected institute's closed intranet platform. The external data were open MOHW data on the number of daily confirmed COVID-19 cases. After acquiring the students' online learning data, the researchers first performed data cleaning and then sorted the daily number of hours of online video learning by group. The sources of internal and external data and the principles of data sampling and processing are described in the following sections.

3.3.1 Data sources

3.3.1.1 Internal data: student online learning database The researchers collected student online learning logs from the LMS for learning analysis. The data included the online video categories and the recorded time spent on watching asynchronous online videos. This information was collected to calculate the total time spent by the enrolled students in viewing asynchronous videos on the online LMS platform.

After eliminating the behavioral data generated by the accounts of the teachers and assistant teachers, 189,646 online learning logs were obtained for the pandemic group (the 2019 academic year) and 44,599 online learning logs were obtained for the control group (the 2018 academic year).

3.3.1.2 External data: government public information To examine the effect of the COVID-19 pandemic on the online learning journeys of the students in the pandemic group, the researchers collected information on the daily number of confirmed COVID-19 diagnoses after March 2, 2020, from the MOHW website (https://sites.google.com/cdc.gov.tw/2019ncov/taiwan). This information was collected to understand the distribution of confirmed COVID-19 cases in Taiwan.

3.3.2 Principles of data processing and sampling

First, data preprocessing was performed on the LMS logs of the time spent by the students in viewing the videos. The researchers eliminated video viewing entries shorter than 3 s to ignore the data collected when students searched for specific passages or played the media by accident.

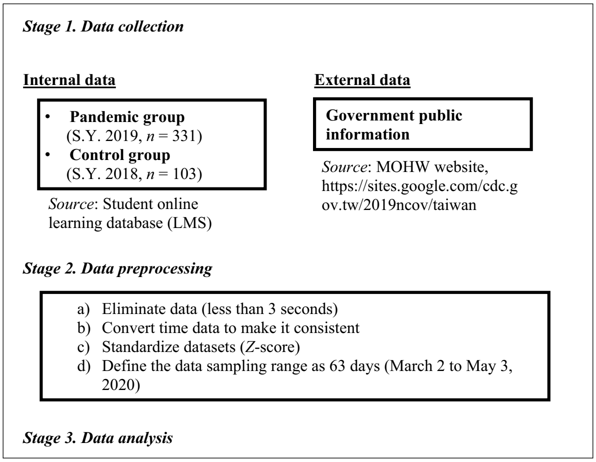

Fig. 2 Research process

Second, because the two student groups had different semester start dates, the researchers converted the time field data to generate a new field, namely the number of days since the start of the semester, to facilitate analysis.

Third, the researchers converted the data of the two groups into standard scores to facilitate subsequent analyses. Linear conversion principles are used to convert one group of data into standardized scores without specific units and concentrations. The statistical significance of converting the Z-score in this study refers to how many standard deviations the original score fell above or below the average score. This conversion was performed to reflect the discreteness of the overall distribution (Chiou & Lin, 2014).

Finally, the researchers defined the study period as being from the beginning of the semester to the end of the week of midterm exams. This period coincided with the peak of the COVID-19 epidemic in Taiwan. Therefore, to facilitate period-to-period comparison, data on the two groups were collected from the beginning of the course to the end of the week of midterm exams. In accordance with the university administrative calendar, the 63 days from March 2 to May 3, 2020, were set as the data sampling range, which is a limitation of this study. Figure 2 presents the research process.

3.4 Statistical methods

R (ver. 3.6.6) was used to analyze the learning data.

3.4.1 Spearman rank correlation test

The first research question examines whether the development of the COVID-19 pandemic affected the online learning behaviors of the students. Because the population of the research sample did not satisfy a normal distribution assumption, Spearman's rank correlation coefficient was used to determine the rank correlations of the data (Wu, 2013). After determining the correlation coefficient (r), the researchers used the effect value to distinguish the effect benchmark corresponding to the correlation coefficient. The effect value is suitable for analysis using the Spearman correlation coefficient.

The benchmarks in this study for small, medium, and large effects were $r=0.1$ (explains 1% of differences), $r=0.3$ (explains 9% of differences), and $r=0.5$ (explains 25% of differences), respectively (Cohen, 1997; Nakagawa & Cuthill, 2007). These benchmarks were used to determine the correlations between the online learning behaviors of the pandemic group and control group.

3.4.2 Wilcoxon signed-rank test

The second research question examines whether differences existed in the online learning behaviors of the two student groups. When the population distribution is abnormal, the Wilcoxon signed-rank test can be used to determine the sign and magnitude of paired data differences (Chen et al., 2012).

The data collected in this study are numerical data with an abnormal distribution; thus, the Wilcoxon signed-rank test is suitable for comparing the online learning behaviors of the two student groups at different stages.

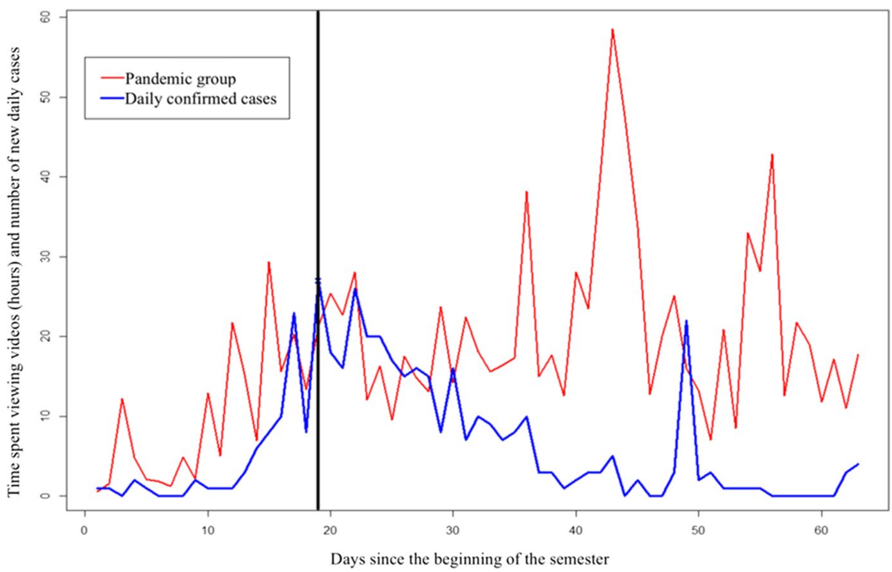

Fig. 3 Daily new COVID-19 cases and online learning behaviors since the beginning of the semester

4 Study results

4.1 Influence of the pandemic on online learning in Taiwan

4.1.1 Correlation test for the COVID-19 peak 19 days after the start of the semester

First, the researchers explored whether the increase in the number of COVID-19 cases in Taiwan affected the online learning behaviors of the students after the semester started on March 2, 2020. According to the collected data, the number of new COVID-19 infections in Taiwan peaked on March 30, 2020. Figure 3 presents a comparison between the amount of time spent by the students in watching online learning videos and the number of daily new COVID-19 infections in Taiwan. The two lines in the aforementioned figure exhibit similar patterns for the 19 days from the start of the semester (March 2, 2020) to the peak of the pandemic in Taiwan (March 20, 2020).

The Spearman rank correlation coefficient results indicated that the students' online learning behaviors from the beginning of the semester until the pandemic peak were correlated with the number of new cases reported daily during the same period ($r > 0.5$). From the peak of the pandemic until the midterm exams ended, the online learning behaviors did not exhibit a correlation with the number of new COVID-19 infections reported in Taiwan ($r = -0.0843$, $p > .05$), as presented in Table 1.

4.1.2 Converting the Z-scores for a three-way comparison

To confirm that the correlation between the online learning behaviors of the students and the number of daily confirmed infections in Taiwan from March 2 to 20, 2020, was not coincidental, the researchers performed correlation analysis on the data of the pandemic and control groups for the same period of 2 academic years. After converting the learning behaviors of the two groups into standard Z-scores, the dates were converted into the number of days since the start of the semester for comparison. The standardized data for the 2 academic years are displayed as a line graph in Fig. 4.

After standardization, the researchers analyzed the correlations among the number of new daily infections in Taiwan, the time spent by the pandemic group in watching online videos, and the time spent by the control group in watching online videos for 19 days since the beginning of the semester. The online learning behaviors of the control group within the first 19 days since the start of the semester did not demonstrate any correlations with the development of the pandemic in Taiwan

Table 1 Results of the correlation tests

Periods	*p* value	Rho
From the beginning of the new semester to the pandemic peak (March 2–20, 2020)	.003**	.6379
From the pandemic peak to the end of the midterm exams (March 21–3 May, 2020)	.5865	− .0843

*$p < .05$, **$p < .01$, ***$p < .001$

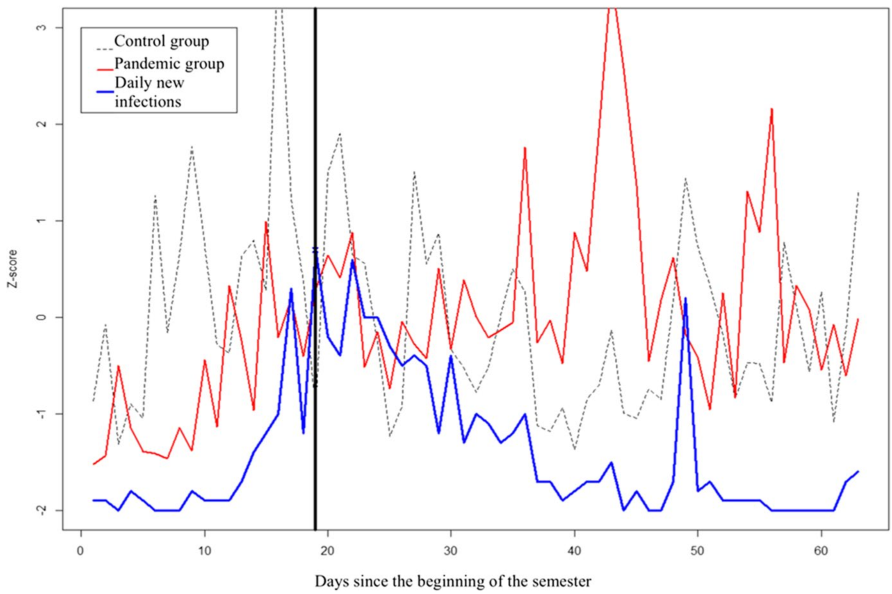

Fig. 4 Variations in the number of new daily infections in Taiwan and in the time spent by the pandemic and control groups in watching online videos

Table 2 Results of three-way comparison

Comparisons for the first 19 days of the semester	*p* value	Rho
Control group versus pandemic trend in Taiwan	.3278	.2374
Pandemic group versus pandemic trend in Taiwan	.003***	.6379
Control group versus pandemic group	.6728	.1035

*$p<.05$, **$p<.01$, ***$p<.001$

($r=0.2374$, $p>.05$). Furthermore, the online learning behaviors of the control group exhibited low correlation with those of the pandemic group during the first 19 days since the start of the semester ($r=0.1035$, $p>.05$), as presented in Table 2. The aforementioned results indicate during the first 19 days of the school semester, the development of the COVID-19 pandemic exerted a considerable effect on the pandemic group's online learning behaviors.

4.2 Changes in the online learning behaviors of the pandemic group after the decline of the COVID-19 pandemic in Taiwan

The aforementioned results indicate that the development of the COVID-19 pandemic in Taiwan had a considerable effect on the pandemic group's online learning behaviors until the pandemic peaked. On March 21, 2020, the number of daily new infections in Taiwan began to decrease. Therefore, the researchers examined the effect of the decline in the pandemic from the aforementioned date until the midterm exams (May 3, 2020) on the students' online learning behaviors. Same-period analysis was conducted for the pandemic and control groups in which a difference test was performed. The results of the difference test were then combined with descriptive data on the number of seconds spent by each student in watching online videos each day to determine the effects of the pandemic background and pandemic-caused environmental stress on the students' online learning behaviors.

4.2.1 Differences between the pandemic and control group

Same-period analysis was conducted on the online learning behaviors of the two student groups from the 20th day since the start of the school semester until the midterm exams. Considering the abnormality of the two datasets and the small sample sizes, researchers calculated Spearman's rank correlation coefficient for testing. The results indicated that from the 20th day since the start of the school semester until the midterm exams, a significant difference existed between the online learning behaviors of the two groups ($p < .01$). The descriptive statistics indicate that the pandemic group students viewed videos for an average of 250.10 s per day, and the control group students viewed videos for an average of 240.89 s per day (Table 3).

To determine the differences in the students' online learning behaviors at different times, the researchers performed difference testing and compared the descriptive statistics for weekdays and daytime with those for weekends and nighttime, respectively.

4.2.2 Weekday–weekend comparisons

4.2.2.1 Weekday differences Before conducting same-period comparisons, the researchers converted the Z-scores of the weekday learning behaviors of the two student groups and then selected the online learning data for the corresponding days for the Wilcoxon sign-rank test. In this study, weekdays were defined as Monday to Friday. Considering the abnormality and small sample size of the data, the data were tested using Spearman's rank correlation coefficient. The results indicated that from the 20th day since the start of the semester until the midterm exams, the two student groups exhibited significant differences in their weekday online learning behaviors

Table 3 Differences between the two student groups

Differences between the two student groups	Wilcoxon (p value)	Control group	Pandemic group
20 days since the start of the semester until the midterm exams	0.0011**	240.89	250.10

$p < .05$ **$p < .01$ ***$p < .001$

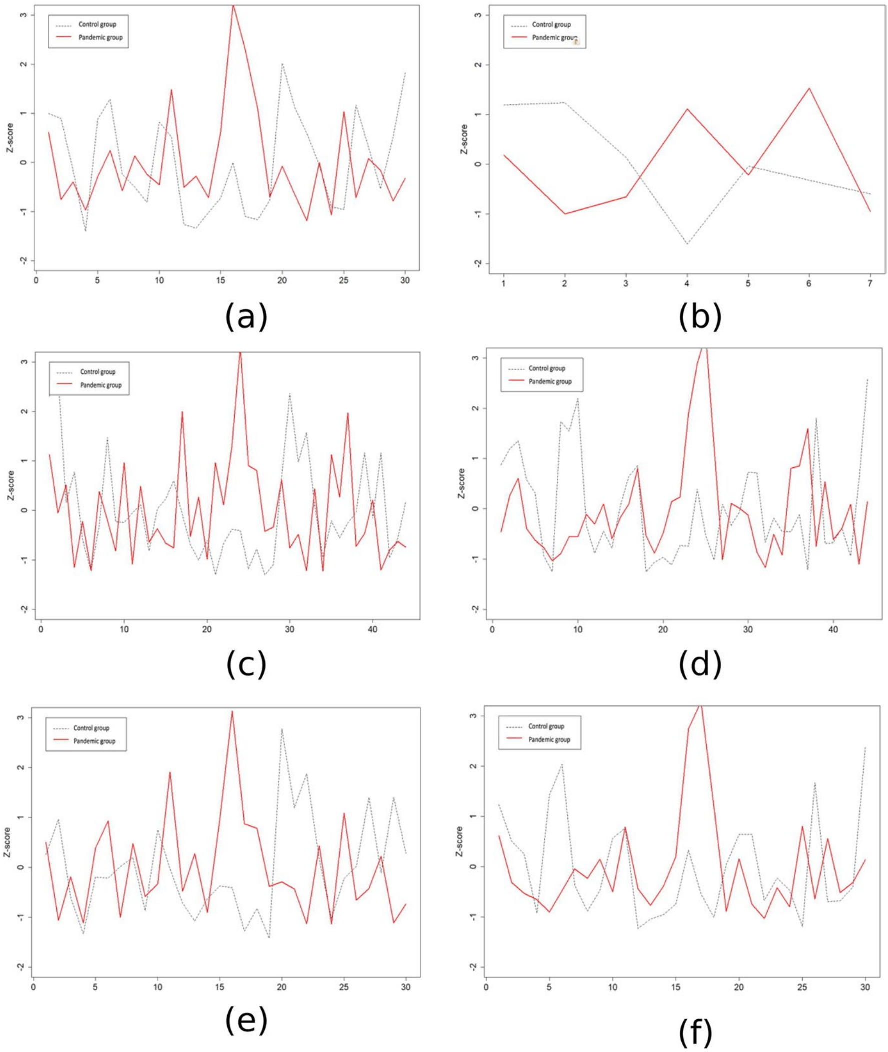

Fig. 5 Z-scores of the student online learning behaviors. **a** After the COVID-19 peak—weekdays: 100 students in the control group and 304 students in the pandemic group; **b** after the COVID-19 peak—weekends: 78 students in the control group and 249 students in the pandemic group; **c** after the COVID-19 peak—daytime: 93 students in the control group and 292 students in the pandemic group; **d** after the COVID-19 peak—nighttime: 91 students in the control group and 292 students in the pandemic group; **e** after the COVID-19 peak—daytime on weekdays: 89 students in the control group and 267 students in the pandemic group; and **f** after the COVID-19 peak—nighttime on weekdays: 87 students in the control group and 262 students in the pandemic group. The dotted lines represent the results of the control group, and the solid lines represent the results of the pandemic group

($p < .01$). The descriptive statistics indicate that the pandemic group students viewed videos for an average of 265.77 s, and the control group viewed videos for an average of 254.37 s (Fig. 5 and Table 4).

Table 4 Weekday comparisons

Differences between the two student groups	Wilcoxon (p value)	Control group (n = 100)	Pandemic group (n = 304)
20th day since the start of the semester until the midterm exams	.0106*	254.37	265.77

$p < .05$ $^{**}p < .01$ $^{***}p < .001$

4.2.2.2 Weekend comparisons In this study, weekends were defined as Saturday and Sunday. Due to the limited number of weekend samples, statistical verification was not possible. The descriptive statistics indicate that for the same period, the pandemic group students viewed asynchronous online videos for a longer average duration per day than the control group students did (344.37 s vs. 324.75 s), as presented in Fig. 5 and Table 5.

4.2.3 Daytime and nighttime comparisons

The researchers also examined the online learning behaviors during designated daytime and nighttime intervals. Daytime was defined as being from 08:00 to 19:00 on the same day, and nighttime was defined from being from 19:00 to 08:00 on the next day. The researchers verified the differences between the results of the two student groups from the 20th day since the start of the semester until the midterm exams for the aforementioned time intervals. They also investigated the changes in the patterns of the students' online learning behaviors.

After converting both groups' daytime and nighttime learning behaviors into Z-scores, a Wilcoxon sign-rank test was performed on the online learning data for the aforementioned time intervals. The results indicated that significant differences existed in the daytime online learning behaviors of the pandemic and control groups ($p < .01$); however, no significant differences were exhibited in the nighttime learning behaviors of the aforementioned groups ($p > .05$).

The descriptive statistics indicate that the pandemic group students viewed asynchronous online videos for a longer average duration per day than the control group students did (157.47 s vs. 141.22 s). Alternatively, during the nighttime, the control group students viewed asynchronous online videos for a longer average duration per day than the pandemic group students did (133.94 s vs. 127.07 s), as presented in Fig. 5 and Table 6.

Table 5 Weekend comparisons

Differences among the two groups	Control group (n = 78)	Pandemic group (n = 248)
20th day since the start of the semester until the midterm exams	324.75	344.37

Table 6 Daytime and nighttime comparisons

Differences between the two student groups	Wilcoxon (*p* value)	Control group (day n = 93) (night n = 91)	Pandemic group (day n = 292) (night n = 292)
Daytime	.0085**	141.22	157.47
Nighttime	.0715	133.94	126.07

$p < .05$ **$p < .01$ ***$p < .001$

4.2.4 Weekday daytime and nighttime comparisons

Immediately after the COVID-19 outbreak in Taiwan, the institution selected in this study implemented a series of synchronous and asynchronous online alternatives for their physical courses. Therefore, compared with the same period preceding the COVID-19 outbreak, students had more opportunities to use the institute's digital learning platform after the outbreak. Therefore, the researchers investigated whether the increased opportunities to use the digital learning platform led to differences in learning behaviors between the two student groups from the 20th day since the start of the semester until the midterm exams.

After converting both groups' daytime and nighttime learning behaviors into Z-scores, a Wilcoxon sign-rank test was performed on the online learning data for the daytime and nighttime. Significant differences were observed in the weekday daytime online learning behaviors of the pandemic and control groups ($p < .01$); however, no significant differences were found in the weekday nighttime online learning behaviors of the two groups ($p > .05$).

The descriptive statistics indicate that during weekday daytime intervals, the pandemic group students viewed asynchronous online videos for a longer average duration per day than the control group students did (172.54 s vs. 144.03 s). Conversely, during weekday nighttime intervals, the control group students viewed asynchronous online videos for a longer average duration per day than the pandemic group students did (149.69 s vs. 140.03 s), as presented in Fig. 5 and Table 7.

Table 7 Comparison between the daytime and nighttime results on weekdays

Differences between the two groups	Wilcoxon (*p* value)	Control group (daytime n = 89) (nighttime n = 87)	Pandemic group (daytime n = 267) (daytime n = 262)
Daytime on weekdays	.0061**	144.03	172.54
Nighttime on weekdays	.1568	149.69	140.03

$p < .05$ **$p < .01$ ***$p < .001$

5 Conclusion

During the COVID-19 pandemic, governments have been forced to close down schools, which have transitioned to remote teaching in order to reduce the risk of infection among teachers and students. However, the pandemic at large has continued to weigh on students' mental health (Copeland et al., 2021; Fawaz et al., 2021; Guessoum et al., 2020). This study explored whether students' online learning behaviors in an asynchronous learning environment have changed because of the ongoing pandemic. The correlation analysis and period-to-period comparisons revealed that during the 19 days until the peak of the pandemic was reached, the students' online learning behaviors were correlated to with the increase in daily confirmed cases of COVID-19 in Taiwan. A survey on how the pandemic has affected student learning reported that approximately 25% of the participants exhibited a positive correlation between their anxiety symptoms and concerns about learning delays during the pandemic (Cao et al., 2020). Further analysis of the survey result indicated that this phenomenon was attributable to how university students enrolled in asynchronous remote courses became anxious from receiving daily updates about the pandemic from online media and converted that anxiety into active response actions, which in this case, was the proactive viewing of online video materials. Heffer and Willoughby (2017) also agreed individuals who effectively adopt coping skills can more effectively process challenging situations and reduce harmful emotions. Furthermore, observing university students' online learning trajectories did not reveal any signs of lax learning or collective relaxation due to the easing of the pandemic in Taiwan; the weekday, daytime, and weekday daytime groups significantly outperformed their period-to-period counterparts. The descriptive statistics of the weekend period also demonstrated a similar trend in which the pandemic group exhibited more favorable performance. The findings of this study supplement the research results of Schreiner (2010), which indicated that a student's ability to thrive is strongly affected by their environment and overall emotional well-being. The present study also provided preliminary evidence on how pandemics affect students' asynchronous online learning.

Several implications can be obtained from the results of this study. First, this study highlighted the differences in the behaviors of university students enrolled in asynchronous remote courses during pandemic and nonpandemic periods. Studies have demonstrated correlations between the development of a pandemic and students' online learning. Second, the results provided a further insight into how students continue to learn in asynchronous remote courses as the external environment is continually affected by the pandemic. When teachers attempt to convert physical courses into synchronous remote learning to maintain educational activities, they can observe asynchronous remote courses, which allow students more autonomy over their learning and more flexibility with their time, and analyze the backend database records to better understand students' learning responses during the pandemic. Third, the results of this preliminary study can provide universities and educational authorities with information to support their assessment of whether to increase the proportion of asynchronous remote courses and assist students in completing their coursework during school closures. We suggest that during school closures, higher education institutions should maintain the quality of online learning and consider how changes to the external environment affect students' learning, thereby improving their learning efficiency.

6 Limitation

One limitation of this study was the inability to conduct experimental manipulations in advance. Therefore, the constraints on this study must be recognized and resolved in future research. Another constraint is that the learning process data was collected only from students of a single university in Taiwan who were enrolled in asynchronous online courses. Future research should expand the sample by recruiting participants from multiple schools, from K–12, or from different countries or cultural contexts. By using a larger sample and comparing different educational methods, researchers can gain a deeper understanding of the interaction between students' experiences during pandemic development and their online learning.

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Data availability Data are available from the corresponding author.

Declarations

Conflict of interest We have no conflict of interest to declare.

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