Lin, C-H., Wu, W.-H., & Lee, T.-N. (2022). Using an Online Learning Platform to Show Students' Achievements and Attention in the Video Lecture and Online Practice Learning Environments. *Educational Technology & Society*, *25* (1), 155-165.

Using an Online Learning Platform to Show Students' Achievements and Attention in the Video Lecture and Online Practice Learning Environments

Chih-Hung Lin[1], Wun-Hau Wu[2] and Tsu-Nan Lee[3*]

[1]Master Program in Mathematics and Science Education, Department of Education, National Chiayi University, Taiwan // [2]Chiayi County Jhuci Senior High School, Taiwan // [3]Taipei Municipal Linong Elementary School, Taiwan // chuck@mail.ncyu.edu.tw // willy76616@gmail.com // tedbob51@gmail.com

[*]Corresponding author

ABSTRACT: During the worldwide pandemic of coronavirus disease 2019 (COVID-19 pandemic), online learning is increasingly vital for students to learn at home, and online learning platforms provide learning opportunities to students. The Junyi Academy online platform is an online learning platform that both helps lower-achieving students review lessons and helps teachers in Taiwan do differentiated instruction. Several studies have shown the relationships between students' attention and their academic achievements for students' self-learning, but how to best use these platforms to help students learn by themselves is unclear. Therefore, this study investigates the relationships between students' attention and their academic achievements with two online learning environments. A total of 38 upper secondary students in Taiwan to participate in this study, and these students were divided between a Khan-style video lecture (VL) group and an online practice (OP) group. This study adopted an experimental design with data collected by an electroencephalogram (EEG). The results show that students' attention in the VL group was higher than in the OP group. Furthermore, their attention in three stages differed between the two groups. Student attention was similar in the two groups for the first stage, but the VL group had higher attention for the second and third stages was than did the OP group. In addition, there was no relationship between students' attention and their academic achievements in the VL and OP groups. Finally, this study raised some suggestions the future research.

Keywords: Attention, Video lecture, Online practice, Online learning platform, Electroencephalogram (EEG)

1. Introduction

The Programme for International Student Assessment (PISA) has analysed the relationships between students' socio-economic status and their mathematics achievements since 2012, finding that students' achievements in some countries, including Taiwan, could be predicted by their socio-economic status (SES) (OECD, 2014). To reduce the gap between high- and low achieving students, Taiwanese government promotes some programs, such the Project for the Implementation of Remedial Instruction and the Educational Priority Area program, to enhance low-achieving student achievements, Sung et al. (2014) adopted a time series analysis to determine whether participating in these programs could improve student achievements. This study found that the achievement gap in Taiwan increased between higher- and lower-SES. Both results in PISA from 2012 (OECD, 2014) and Sung et al. (2014) showed a similar trend between student achievements and their parents' SES. Therefore, the Taiwanese government has expended much effort to reduce the gap between high- and low achieving students, and OECD (2018) indicated that the gap between students' achievements and their parents' SES has been reduced in Taiwan. However, SES is still a strong predictor to explain 13% of the variation in Taiwanese students' mathematics achievements (OECD, 2020). This may be because higher-SES students have better educational resources. Hwang (2015) pointed out that many secondary students in Taiwan go to cram schools after school, but many lower-SES students' parents could not afford the extra tuition fee. Thus, online learning materials on e-learning platforms, such as the Junyi Academy online platform, are useful to help lower-SES students review lessons, and schools in Taiwan also provide relevant hardware, such as tablets, to help these students review lessons at home after school.

After the global COVID-19 pandemic began in early 2020, the World Health Organization announced that people should maintain social distancing and wear a mask both indoors and outdoors (World Health Organization, n.d.). In addition, schools have closed to limit the spread of this disease in numerous countries, limiting students' learning opportunities, so many schools in these countries use synchronous online teaching to help students learn at home (Bailey et al., 2020; Jan, 2020). Although there were only 799 confirmed COVID-19 cases in Taiwan by the end of 2020, Taiwan's government still encouraged each school to simulate school closures and demonstrate how to teach/learn at home (Ministry of Education, n.d.). Taiwan's Ministry of Education (n.d.) suggests several ways to teach/learn at home, including using Google Meet, Microsoft Teams, and several e-learning platforms. The Junyi Academy online platform is one of e-learning platforms and aims to help educators teach students in accordance with their aptitude and to motivate their interest in learning (Junyi Academy, n.d.). Under COVID-19 restrictions, this online platform is used to help primary and secondary

ISSN 1436-4522 (online) and 1176-3647 (print). This article of the journal of *Educational Technology & Society* is available under Creative Commons CC-BY-NC-ND 3.0 license (https://creativecommons.org/licenses/by-nc-nd/3.0/). For further queries, please contact Journal Editors at ets.editors@gmail.com.

students learn at home, but how to use these platforms appropriately to enhance student achievement is still unclear to many teachers.

Students' academic achievements is affected by several factors, one of which is their attention since it can determine academic achievement (Bester & Brand, 2013; Chang et al., 2019; Shadiev et al., 2017). Attention is defined as the limitations in processing information and how people monitor these limitations. The five types of attention are focusing, perceptual enhancement, binding, sustaining behaviour, and action selection (Medin et al., 2005). Each type of attention explains a different aspect of attention, and this study considers attention as sustained attention, which is when someone pays attention to salient objects and excludes other objects for a certain amount of time (Medin et al., 2005). In online learning environments, students may have interference from other icons or pop-up messages, and their sustained attention would indicate their concentration on learning. Online learning environments have pros and cons for student learning. On one hand, Terras and Ramsay (2015) indicate that students are able to watch online video lectures repeatedly to increase learning opportunities. On the other hand, Lodge and Harrison (2019) find that using technology to learn has a negative impact on the brain. In addition, Lin and Chen (2019) show that students using online video lectures to learn might ignore important content, and Chen et al. (2017) state that students would be distracted without teacher supervision in online learning environments. However, using online learning environments is indispensable during the current COVID-19 pandemic. Therefore, this study investigates relationships between students' attention and their academic achievements in different online learning environments. Accordingly, three research questions are addressed in the next section.

1.1. Research questions

(1) What were differences between students' pre-test and post-test scores under two types of online learning environments?
(2) What were differences in students' attention at different learning stages in two types of online learning environments?
(3) What were relationships between students' attention and their academic achievement in two types of online learning environments?

2. Theoretical frameworks

This section introduces relevant theories to analyse two types of online learning environments, video lecture and online practice, as used in the Junyi Academy online platform. Then empirical studies examine relationships between students' academic achievements and their attention in online environments.

There are two main theories to describe students' multimedia learning. One is the cognitive theory of multimedia learning (CTML, Mayer, 2014) and the other one is cognitive load theory (CLT, Paas & Sweller, 2014). Both theories are related to the limitations of working memory and the capacity of working memory determines how students select information, and information selection is associated with sustained attention. CTLM explains interactions between pictures and text on students' learning (Mayer, 2014), whereas CLT outlines three categories of instructional design to reduce students' working memory load, including extraneous, intrinsic and germane cognitive load (Paas & Sweller, 2014). Different online learning environments could be based on different theories. In this study, two types of online learning environments are considered in the Junyi Academy online platform. One type is "video lecture (VL)," and the other type is "online practice (OP)." The type of video lecture in Junyi Academy online platform is referred to as a "Khan-style video lecture," and Chen and Wu (2015) define "the Khan-style video lecture" as a handwritten tutorial with digital pens and tablets with an audio voice to explain content. Students would not see a lecturer's face and no gestures guide students to see what content is important in this online learning environment. Students have to pay attention to hear what lecturers say and follow the lecturers' voice to learn. For online practice, the Junyi Academy online platform posts a problem for students to solve once, and there is a yellow icon to provide hints to help solve problems. Students can solve problems on real paper and submit an answer online in this environment.

According to both online learning environments, the Khan-style video lecture is related to a teaching method and could be explained by the extraneous cognitive load. The extraneous cognitive load represents that information is given by instructional designers, and the way of giving information is related to teaching activities (Chandler & Sweller, 1991). This means that lecturers in the Khan-style video lecture environment have selected relevant information to demonstrate to students. However, students in the Khan-style video lecture environment have to use visual and auditory channels to learn, and Ayres and Sweller (2014) indicate that using both channels to learn would increase students' cognitive load due to the need to coordinate information from different channels. This implies that students might have to pay attention closely to learn in the Khan-style video lecture, and thus spend more cognitive load to learn (Chen & Wu, 2015). Online practice is different from the Khan-style video lecture since an interface in the online practice learning environment only shows a problem with yellow and green icons (see Figure 2). When students click the yellow icon, a hint is shown by Arabic numerals in yellow, so students solve problems easily. The design of the online practice learning environment followed the signalling principle in CTML (Mayer, 2014). Glaser et al. (2017) claim that signalling can help students organize information. The yellow icon with relevant solutions guides students to organize information in order to solve problems. Therefore, the yellow icons with relevant hints are signals to highlight relevant points in an online practice environment. Kalyuga et al. (1999) claim that using signalling to design an online environment could reduce the load on students' working memory, and this study hypothesises that students in an online practice environments might require less cognitive load to learn. In sum, students have more cognitive load in the Khan-style video lecture environments, whereas students in the online practice environments could use less cognitive load to learn effectively.

2.1. Students' attention and their academic achievements

As in the theories of multimedia learning discussed above, cognitive load is related to sustained attention, and there are three approaches to evaluate people's sustained attention in online learning environments, including an electroencephalogram (EEG), eye tracking and paper-and-pencil tests. Detecting people's sustained attention generally uses an EEG test with NeuroSky's MindWave earphone, and the EEG signal data from the NeuroSky has been validated (Chen & Huang, 2014; Chen & Wang, 2018; Chen et al., 2017; Chen & Wu, 2015; Shadiev et al., 2017; Sun & Yeh, 2017; Wu et al., 2020). Numerical data from the EEG signals reflects in real time how many nervous system activities are related to people's sustained attention (Chen et al., 2017). Higher values from the EEG indicate higher attention. However, relationships between attention and academic achievements show inconsistent conclusions in different learning environments. The relationships between students' academic achievements and their attention are discussed below to show which factors might influence these relationships:

Students using online learning environments could have higher academic achievement and higher-level attention than those in traditional environments. Chang et al. (2019) compared a traditional PowerPoint lecture with the massive online courses (MOOCs) in lower secondary students' attention and their academic achievements, and this study found that students using MOOCs could have higher achievement and higher-level attention. Shadiev et al. (2017) used technology to teach English, finding that university students using technology had higher attention by EEG and had better learning performances in comparison with students without using technology to learn English. Although online learning environments have advantages for learning, they need extra support to help students concentrate on learning. Chen and Wang (2018) indicated that students who had extra support (monitoring and alarm mechanisms) in online environments would get more attention and have better academic achievement.

However, more attention might not lead to better academic achievement because of students' cognitive load. Although Chen and Wu (2015) showed that university students' performed similarly after different online learning environments, the current study finds that students viewing slides with a lecturer's voice and image had to use more cognitive load than students viewing slides without a lecturer's voice. Furthermore, Wu et al. (2020) compared digital game-based learning environments (DGLE) and static E-learning environments (SELE), and found that university students' attention and achievement in the two groups were similar. Wu et al. (2020) indicated that students were interested in DGLE and DGLE could trigger students' learning motivation, but DGLE was more complex and increased students' cognitive load. A complex learning environment might overload students' cognitive capacity. Both Chen and Wu (2015) and Wu et al. (2020) imply that more complex online environments lead to higher attention, though higher attention does not necessarily bring better academic achievements.

The relationships between students' attention and their academic achievements are still debated, but these relationships might be associated with student age. Chen and Wang (2018) and Sun and Yeh (2017) developed attention-monitoring systems for online learning environments. While students in Chen and Wang (2018) were lower secondary students, Sun and Yeh (2017) used university students. Both studies found that students experiencing attention monitoring systems had higher attention, but students' achievements showed different patterns. The different patterns could be explained by differences in cognitive executive functions. Youths' cognitive executive functions are still developing before 13 years old (Davidson et al., 2006). Although students in Sun and Yeh's (2017) study without attention monitoring systems had lower attention, these students could rely on their relevant prior knowledge and working memory to do a post-test. Their cognitive executive functions are mature and could overcome their lower attention to get acceptable scores in the post-test. In Chen and Wang (2018), primary students' cognitive executive functions were still developing, so their prior knowledge and working memory were limited. This might explain why primary students with higher attention could get better academic achievement, while mature students could be supported by their prior knowledge and relevant experiences in an achievement test.

According to the aim of the Junyi Academy online platform mentioned above, this platform has a Khan-style video lecture and online practice for each student, to choose and their cognitive load should be different in using the two online environments. This study reveals some potential research values. Some studies (Chang et al., 2019; Chen & Wang, 2018; Chen et al, 2017; Chen & Wu, 2015; Lin & Chen, 2019) used an EEG to detect sustained attention in video lecture online environments, and most studies (Chang et al., 2019; Chen & Wang, 2018; Chen et al., 2017; Chen & Wu, 2015) analysed an effect of instructional immediacy. However, only Lin and Chen (2019) discussed the learning effect after reviewing, using EEG to detect 55 primary students' attention and their achievements after reviewing. That study used an attention-based video lecture review mechanism (AVLRM) to evaluate student achievement and found that only low-attention students using AVLRM had higher achievement than without using AVLRM. In addition, students' attention in online practice environments is evaluated by eye-tracking (Glaser et al., 2017). Overall, few studies have evaluated the learning effect after reviewing, and no study has used the EEG to find effects of the signalling principle. This study provides relevant empirical data to expand the theoretical basis of multimedia learning techniques.

3. Research methods

This section describes participants, materials, procedures and data analysis in order to fulfil the goals of this study and research questions. It also demonstrates how this study answers these research questions.

3.1. Participants

All participants in this study were from the same regional secondary school in Chiayi County, Taiwan. Fifty Taiwanese secondary students were recruited for this study. This study also informed consent from the students and their families. Students with pre-test scores higher than 17 points were excluded, leaving thirty-eight participants for the study. Twenty-four grade 11 students and fourteen grade 12 students were randomly assigned the video lecture (VL) and the online practice (OP) groups. Each group had 19 students. In the pre-test, students' scores had no significant difference by both types of online learning environments and grades, online learning environments: $t(36) = .17$, $p = .839$, Cohen's $d = .066$; grade: $t(19.50) = 1.49$, $p = .154$, Cohen's $d = .664$. Thus students' pre-test scores for the two types of online learning environments and grades were similar. Students' pre-attention had also no significant difference for the two types of online learning environments and grades, online learning environments: $t(36) = 1.13$, $p = .267$, Cohen's $d = .366$; grade: $t(36) = .17$, $p = .863$, Cohen's $d = .058$. Thus students' attention spans before reviewing lessons online were similar. Students' pre-test scores and pre-attention are shown in Table 1.

Table 1. Students' pre-test scores and pre-attention in the two types of online learning environments and grades

Types	Video Lectures (VL)				Online Practice (OP)			
Grade	Grade 11		Grade 12		Grade 11		Grade 12	
Number	11		8		13		6	
	Test	Attention	Test	Attention	Test	Attention	Test	Attention
M	16.09	41.70	12.75	39.07	14.46	44.80	15.50	47.23
SD	1.70	15.68	4.10	15.43	2.88	12.07	3.62	11.93

3.2. Materials

The midsegment theorem was the main topic in this study, using the VL and OP groups to present this theorem. The topic of the midsegment theorem was introduced in grade 9, and students apply this theorem for trigonometric functions in grade 11 (Ministry of Education, 2014). Although upper secondary students should understand the midsegment theorem, grade 11 students must review this theorem to help them learn the trigonometric functions, and grade 12 students could review it for the university entrance exam. In this study, the midsegment theorem was for reviewing in grades 11 and 12 students. In the VL group, a lecturer first introduces the midsegment theorem first and then demonstrates two problems to solve. Students in the OP group receive 10 to 20 problems to solve. Students who could not finish any of these problems could click an icon to show how to solve problems. For students who still could not solve these problems, their computer screen would have pop-up part to show a hint. After a problem is solved correctly, the online system shows the next problem. Materials in both the VL and OP group were from the Junyi Academy online platform. The interface samples of the VL and OP groups are shown in Figure 1 and 2, respectively.

Figure 1. Presentation in the VL group

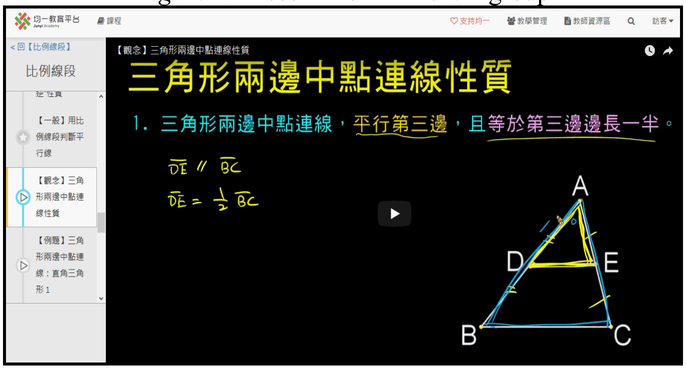
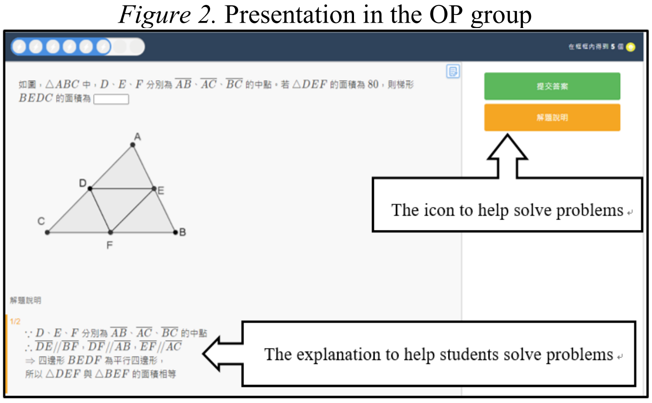


Figure 2. Presentation in the OP group



To understand students' academic achievement, this study adapted an achievement test from the Junyi Academy online platform. The test had 21 items, and all items' item discrimination index (D value) should be higher than 0.4. According to this criterion, this study did the pilot study from 52 students' responses. The result showed that there were two items which should be excluded because their D values were lower than 0.4. Therefore, only nineteen items were in the achievement test, with D values ranging from 0.46 to 0.92. Each item had 1 point, so the full score in this test was 19 points. Validity was verified by experienced high school mathematics teachers, and the reliability was .86. It was used as both a pre- and post-test.

Physiological signals were used to evaluate students' levels of attention. The instrument, as shown in Figure 3, is a brainwave sensing headset to act as an electroencephalogram (EEG) from NeuroSky technologies. Students wear the headset with a sensor and the sensor receives students' brainwaves and transmits them to a computer through Bluetooth. Output values are from 0 to 100, with higher values indicating higher levels of attention.

Figure 3. Brainwave sensing headset (NeuroSky, n.d.)

3.3. Procedures

All students took the achievement pre-test with no time limit before online learning. After one week, groups of from 1 to 3 students did online learning in their school's computer lab. In order to understand the baseline of students' attention (pre-attention), all students would wear the headset and close their eyes to relax for 3 minutes. Examiners asked students to open their eyes and start to review the midsegment theorem online within eight minutes. After reviewing online, the students took the same achievement test as a post-test. Instructions for the VL and OP groups were as follows: (1) For the VL group's students: "This experiment has three stages. The first stage is to help review what the midsegment theorem is, and the second and third stages each have one problem to solve. You have eight minutes to review online, and you should move the screen cursor to check your learning progress." After reviewing online, the examiners would ask students do the post-test. (2) For the OP group's students: "This experiment has three stages, and each stage has different problems to solve. You have eight minutes to solve problems. If you do not know how to solve these problems, you can click a yellow icon to get some hints.

3.4. Data analysis

This study used an experimental design to understand the effects of different types of online learning environments on students' attention and academic achievement. As three research questions were addressed, this study used repeated measure ANOVA for research questions 1 and 2, and correlation analysis for research question 3. For research question 1, this study used students' pre- and post-test scores in the achievement test to compare the two types of online learning environments by analysing the repeated measure ANOVA. The types of online learning environments and the pre- and post-test were independent variables, and scores in the pre- and post-test were dependent variables. For question 2, this study divided the experiments into three sections, with students in different groups having different sections. For the VL groups, introducing the midsegment theorem was the first section, and demonstrating two problems were the second and third sections. The cut points in the two sections were 3 minutes 25 seconds, 5 minutes to record students' attention. The first stage was 0 to 3 minutes 25 seconds, the second stage is from 3 minutes 25 seconds to 5 minutes, and the third stage is longer than 5 minutes. For students in the OP group, the cut points were the same as the VL group. The recording students' attention was recorded in seconds. The types of online learning environments and the three stages were independent variables, and the value of students' attention in three stages was the dependent variable. This research question also used repeated measure ANOVA to show the trend of students' attention in three stages for the two types of online learning environments. According to the variables in research questions 1 and 2, the data of student scores in the achievement test and the value of attention were numerical data, while the different types of learning environments and the pre- and post-test were categorical data. For research question 3, this study used correlation analysis to determine the relationships between student achievement and attention in the two types of online learning environments. Students' post-test scores were their achievement and students' overall attention from the EEG data was their attention. Both student achievement and attention were numerical data. Correlation analysis showed whether students' attention had a positive effect on student achievement

4. Results

Statistical analysis was used to answer the research questions, and this section has three parts to consider each question

4.1. Research question 1

Two-way repeated measure ANOVA was used to answer research question 1. Box's test for equivalence of covariance matrices showed no significant difference, with Box's $M = 5.25$, $F(3, 233280) = 1.64$, $p = .177$. Thus variances in students' pre- and post-test scores were similar, and the data could use the two-way repeated measure ANOVA to test. Results showed that students' scores for pre- and post-test had a significant difference, $F(1, 36) = 11.60$, $p = .002$, $\eta^2 = .244$, and student scores in the post-test were higher than their pre-test. However, there was no significant difference between two types of online learning environments, $F(1, 36) = .004$, $p = .949$, $\eta^2 = .000$. Meanwhile, there was no interaction effect between student scores in the pre- and post-test and different types of online learning environments, $F(1, 36) = .35$, $p = .561$, $\eta^2 = .009$. This indicates that students' scores between the pre- and post-test in the VL and OP groups were similar and students' scores between the pre- and post-test were not influenced by different online learning environments. Descriptive statistics are shown in Table 2.

Table 2. Descriptive statistics for students' pre-and post-test scores with the two types of online learning environments

Types	Video Lectures (VL)		Online Practice (OP)	
Test	Pre-test	Post-test	Pre-test	Post-test
M	14.68	15.95	14.47	16.62
SD	3.32	2.70	3.03	2.38

4.2. Research question 2

To answer research question 2, this study used the same statistical method as for research question 1. Box's test for equivalence of covariance matrices showed no significant difference, with Box's $M = 7.80$, $F(6, 9389.90) = 1.18$, $p = .313$. Thus the variances in students' attention were similar, and the data could use the two-way repeated measure ANOVA. The results showed that students' attention in all three stages had no significant difference, $F(2, 72) = .60$, $p = .554$, $\eta^2 = .016$, but students' attention between different online learning environments had a significant difference, $F(1, 36) = 13.50$, $p = .001$, $\eta^2 = .273$. Meanwhile, students' attention in three stages and using different online learning environments showed an interaction effect, $F(2, 72) = 4.26$, $p = .018$, $\eta^2 = .106$. Therefore, the simple main effect was needed to understand which factor to determine the interaction effect.

This study used a t-test and ANOVA to test the simple main effect of students' attention between each stage and two types of online learning environments. For the VL group's attention, student attention between three stages had no significant difference, $F(2, 36) = 1.02$, $p = .371$, $\eta^2 = .054$. Thus students' attention in the VL group between three stages was similar. For the OP group' attention, students' attention between three stages had a significant difference, $F(2, 36) = 5.40$, $p = .009$, $\eta^2 = .231$. This showed that students' attention in the OP group between three stages was different, and post hoc analysis was used for the OP group. Student attention in the first stage was better than in the second and third stages, but there was no difference in attention between the second and third stages. Thus the OP group students in the first stage could pay more attention than in the second and third stages. The results indicated that students in the first stage were more attentive than in the second and third stage, but their attention levels in the second and third stages were similar for the OP group's students. Thus students' attention in the VL group was similar between three stages, but students' attention in the OP group had different patterns since students were more attentive in the first stage, and less so in the second and third stages.

Students' attention in the second and third stages had significant differences; second: $t(36) = 3.58$, $p = .001$, Cohen's $d = 1.163$; third: $t(36) = 4.72$, $p < .001$, Cohen's $d = 1.531$. In the second stage, students' attention in the VL group was higher than in the OP group. Students' attention in the third stage showed the same pattern. Thus students in the VL group were more attentive than those in the OP group in the second and third stages. However, there was no significant difference in student attention for the first stage between different online learning environments, $t(36) = .87$, $p = .393$, Cohen's $d = .280$. This indicates that students' levels of attention in the first stage were similar for the two types of online learning environments.

According to the results in research question 2, students' attention levels were similar for the VL and OP group in the first stage, and students' attention levels in the three stages were similar in the VL group. For the OP group, students' attention levels decreased in the second and third stages from the first stage. Descriptive statistics are shown in Table 3.

Table 3. Descriptive statistics of student attention in three stages in two types of online learning environments

Types	Video Lectures (VL)			Online Practice (OP)		
Stage	First	Second	Third	First	Second	Third
M	53.95	55.37	56.71	51.83	47.90	48.20
SD	8.11	6.91	6.43	6.97	5.90	6.99

4.3. Research question 3

Table 4 shows descriptive statistics for student achievement and their attention. However, there was no significant correlation between student achievements and their attention in the VL and OP groups, VL: $r(17) =$

.22, p = .364; OP: $r(17)$ = -.14, p = .571. Although the relationships between student achievement and their attention in the VL and OP groups showed different trends, the relationships were irrelevant.

Table 4. Descriptive statistics of student achievement and attention in two types of online learning environments

Types	Video Lectures (VL)		Online Practice (OP)	
Variable	Achievements	Overall Attention	Achievements	Overall Attention
M	15.95	55.37	16.26	49.34
SD	2.70	5.32	2.38	4.90

5. Discussion

This section addresses the research questions to answer with relevant theories and empirical data for discussion

5.1. Students achievement between two types of online learning environments

This study found similar student achievement levels in the VL and OP groups, in contrast to previous studies (Bester & Brand, 2013; Chang et al., 2019; Chen & Wang, 2018; Lin & Chen, 2019; Shadiev et al., 2017). This might be due to differences in learning environments. These studies discussed students' achievements between the online and traditional learning environments or in using the same online learning environment with/without extra supports. However, this study compared two different online environments with the same topic, and the student achievement results in this study are supported by the studies of Chen and Wu (2015), Hew and Lo (2020) and Ilioudi et al. (2013).

These studies (Chen & Wu, 2015; Hew & Lo, 2020; Ilioudi et al., 2013) compared Khan-style video lectures with other types of video lectures to evaluate students' academic achievement. Chen and Wu (2015) indicated that three types of video lectures in their study could improve students' achievements, but students using the Khan-style video lectures did not improve as much as those using recording classroom lectures or the lecturer's image with lecture slides. Ilioudi et al. (2013) compared students' achievements between recorded classroom lectures, Khan-style lectures and a printed book, with results similar to Chen and Wu (2015). Chen and Wu (2015) claimed that the Khan-style video lecture had no better visual layouts to guide students to learn in online environments, and the inappropriate layouts might influence students' learning performance. In addition, Hew and Lo (2020) stated that using Khan-style video lectures with teacher's talking head videos would increase students' achievement scores. Hew and Lo (2020) implied that the Khan-style video lecture should be used as supplementary material to help students review lessons. Ilioudi et al. (2013) also noted that the Khan-style video lecture was not appropriate for students' self-learning because they had no interactive opportunity to ask questions. Thus, the VL online environment could help students review the midsegment theorem, but this online learning environment might have restricted students' learning in some conditions

The OP learning environment could improve students' learning achievement, which could be due to the repetitive practice of traditional learning methods in Taiwan: (Yang & Lin, 2015). The OP learning environments provide several questions to help students review the midsegment theorem, and Taiwanese students also use a similar method to learn mathematics. Icons in the OP learning environment of the Junyi Academy online platform are like scaffolding to help students how to solve mathematical problems. By doing more practice, students have higher achievement. Although this traditional learning method may not be the best way to learn mathematics, it is effective (Mullis et al., 2012). According to the results for research question 1, the VL and OP online environments in this study could both help students recall what they learned, and students could do practice problems and check their answers. This could explain why both online environments could improve students' academic achievement, but the different interfaces in the VL and OP groups might explain student achievements in the two groups.

5.2. Students' attention in the two types of online learning environments

Although student achievement levels in the VL and OP learning environments were similar, students' attention in the two learning environments showed different trends. Overall, students' attention in the VL group was higher than in the OP group, and students' level of attention differed between the second and third stages. Students in the VL group would see a lecturer to explain the midsegment theorem with the lecturer's handwriting and voice only. As stated above, students could have increased their cognitive load for a higher level of attention, as shown by the EEG data. Chen and Wu (2015) state that students using a Khan-style video lecture would have their attention distracted in order to integrate information, thereby inhibiting their learning. Although students in the VL group showed a higher attention, this might be because they needed to focus on integrating relevant information while watching this video lecture. Students in the VL group need to process several pieces of information at the same time, which would increase their load on working memory. Students' attention level reflects how they control visual information in their working memory (Lodge & Harrison, 2019). Students in the VL group had to process visual and auditory information at the same time through dual channels (Mayer, 2014; X. Yang et al., 2020).Taken together, these studies (Chen & Wu, 2015; Mayer, 2014; X. Yang et al., 2020) indicate that students in the VL group needed to follow a lecturer's voice to track his/her handwriting and see graphic images to understand the midsegment theorem. Alpizar et al. (2020) used meta-analysis to show that the online environment with relevant images and texts would increase students' cognitive load. This means that students in the VL online environment would have increased cognitive load due to integrating the voice, handwriting and images. This increased cognitive load might have caused their higher attention.

The interface in the OP learning environment might be designed according to the signalling principle, which would reduce students' cognitive load (Mayer, 2014). Alpizar et al. (2020) also found that using computers together with printed information was a better online learning environment. Students in the OP group would do arithmetic to review the midsegment theorem, and these students needed to calculate on paper and then submit an answer on the platform. Working on paper without mental calculation might reduce students' cognitive load to influence their attention. However, Ilioudi et al. (2013) indicated that students in using technology would initially spend additional time to be familiar with an interface in order to learn it. This could explain why the OP group's students had higher attention in the first stage because they were familiar with an interface in this learning platform. Accordingly, students could use less attention to learn in the OP learning environments.

5.3. Students achievement and attention in the two types of online learning environments

The results for research question 3 differ from previous studies (Chen & Huang, 2014; Chen & Wang, 2018; Lin & Chen, 2019), which might be due to the developmental level of students' cognitive executive functions. Participants in these studies were primary or lower secondary students, whose achievement is still determined by their attention. Students might have learned relevant topics before, and then use their prior knowledge to solve problems in this study. This possibility is supported by Sun and Yeh's (2017), who indicated that whether students' relevant prior knowledge/experience would affect the relationships between their attention and achievement. Students in this study had learned the midsegment theorem, so their prior knowledge would influence the relationships between attention and academic achievements.

6. Conclusions, limitations and future research

This study found that students in the VL group had higher attention when learning, but students in the OP group could use less attention to learn. Both learning environments could enhance student achievement. Although both environments in this study helped students review lessons, this study reveals their pros and cons for learning. The relationships between student achievement and their attention might be influenced by their cognitive executive functions and their prior knowledge. Following the pandemic, educators should consider how to use online environments to help students learn outside of the classroom.

There were some limitations in this study. First of all, there were only 38 participants, so it would be difficult to extend this study's results to other students. Secondly, this study used an existed online learning platform, with limited learning environments, so other variables could not be manipulated for discussion. Finally, this study asked students to finish reviewing within a limited time restriction, which might affect student performance. Accordingly, future research could develop or modify current interfaces to more clearly analyse the relationships between student achievement and attention and help students learn better by themselves. This study used the EEG to detect students' attention in the OP learning environment, and future research could combine the EEG with eye tracking to more closely monitor students' attention.

Acknowledgement

This study is supported in part by the Ministry of Science and Technology of Taiwan under Contract Numbers MOST 108-2511-H-415-005, MOST 109-2511-H-415-004 and MOST 110-2511-H-415-002.

References

Alpizar, D., Adesope, O. O., & Wong, R. M. (2020). A Meta-analysis of signaling principle in multimedia learning environments. *Educational Technology Research and Development, 68*(5), 2095-2119. https://doi.org/10.1007/s11423-020-09748-7

Ayres, P., & Sweller, J. (2014). The Split-attention principle in multimedia learning. In R. E. Mayer (Ed.), *The Cambridge Handbook of Multimedia Learning* (2nd ed., pp. 206-226). Cambridge University Press.

Bailey, D., Almusharraf, N., & Hatcher, R. (2020). Finding satisfaction: Intrinsic motivation for synchronous and asynchronous communication in the online language learning context. *Education and Information Technologies, 26,* 2563–2583. https://doi.org/10.1007/s10639-020-10369-z

Bester, G., & Brand, L. (2013). The Effect of technology on learner attention and achievement in the classroom. *South African Journal of Education, 33*(2), 1-15. https://doi.org/10.15700/saje.v33n2a405

Chandler, P., & Sweller, J. (1991). Cognitive load theory and the format of instruction. *Cognition and Instruction, 8*(4), 293-332. https://doi.org/10.1207/s1532690xci0804_2

Chang, J.-J., Lin, W.-S., & Chen, H.-R. (2019). How attention level and cognitive style affect learning in a MOOC environment? Based on the perspective of brainwave analysis. *Computers in Human Behavior, 100*, 209-217. https://doi.org/10.1016/j.chb.2018.08.016

Chen, C.-M., & Huang, S.-H. (2014). Web-based reading annotation system with an attention-based self-regulated learning mechanism for promoting reading performance. *British Journal of Educational Technology, 45*(5), 959-980. https://doi.org/10.1111/bjet.12119

Chen, C.-M., & Wang, J.-Y. (2018). Effects of online synchronous instruction with an attention monitoring and alarm mechanism on sustained attention and learning performance. *Interactive Learning Environments, 26*(4), 427-443. https://doi.org/10.1080/10494820.2017.1341938

Chen, C.-M., Wang, J.-Y., & Yu, C.-M. (2017). Assessing the attention levels of students by using a novel attention aware system based on brainwave signals. *British Journal of Educational Technology, 48*(2), 348-369. https://doi.org/10.1111/bjet.12359

Chen, C.-M., & Wu, C.-H. (2015). Effects of different video lecture types on sustained attention, emotion, cognitive load, and learning performance. *Computers & Education, 80*, 108-121. https://doi.org/10.1016/j.compedu.2014.08.015

Davidson, M. C., Amso, D., Anderson, L. C., & Diamond, A. (2006). Development of cognitive control and executive functions from 4 to 13 years: Evidence from manipulations of memory, inhibition, and task switching. *Neuropsychologia, 44*(11), 2037-2078. https://doi.org/10.1016/j.neuropsychologia.2006.02.006

Glaser, M., Lengyel, D., Toulouse, C., & Schwan, S. (2017). Designing computer-based learning contents: Influence of digital zoom on attention. *Educational Technology Research & Development, 65*(5), 1135-1151. https://doi.org/10.1007/s11423-016-9495-9

Hew, K. F., & Lo, C. K. (2020). Comparing video styles and study strategies during video-recorded lectures: Effects on secondary school mathematics students' preference and learning. *Interactive Learning Environments, 28*(7), 847-864. https://doi.org/10.1080/10494820.2018.1545671

Hwang, T.-M. (2015). The Studying and striving of secondary students. In S. Hsu & Y.-Y. Wu (Eds.), *Education as Cultivation in Chinese Culture* (pp. 127-148). Springer. https://doi.org/10.1007/978-981-287-224-1_7

Ilioudi, C., Giannakos, M., & Chorianopoulos, K. (2013). Investigating differences among the commonly used video lecture styles. *Proceedings of the WAVe 2013: The Workshop on Analytics on Video-based Learning* (pp. 21-26). CEUR. http://ceur-ws.org/Vol-983/WAVe2013-Proceedings.pdf

Jan, A. (2020). A Phenomenological study of synchronous teaching during COVID-19: A Case of an international school in Malaysia. *Social Sciences & Humanities Open, 2*(1), 100084. https://doi.org/10.1016/j.ssaho.2020.100084

Junyi Academy. (n.d.). *均一教育平台：關於我們 [Junyi Academy online platform: About us].* https://official.junyiacademy.org/about/

Kalyuga, S., Chandler, P., & Sweller, J. (1999). Managing split-attention and redundancy in multimedia instruction. *Applied Cognitive Psychology, 13*(4), 351-371. https://doi.org/10.1002/(SICI)1099-0720(199908)13:4<351::AID-ACP589>3.0.CO;2-6

Lin, Y.-T., & Chen, C.-M. (2019). Improving effectiveness of learners' review of video lectures by using an attention-based video lecture review mechanism based on brainwave signals. *Interactive Learning Environments, 27*(1), 86-102. https://doi.org/10.1080/10494820.2018.1451899

Lodge, J. M., & Harrison, W. J. (2019). The role of attention in learning in the digital age. *Yale Journal of Biology and Medicine, 92*(1), 21-28.

Mayer, R. E. (2014). Cognitive theory of multimedia learning. In R. E. Mayer (Eds.), *The Cambridge Handbook of Multimedia Learning* (2nd ed., pp. 43-71). Cambridge University Press.

Medin, D. L., Ross, B. H., & Markman, A. B. (2005). *Cognitive psychology* (4th ed.). John Wiley & Sons.

Ministry of Education. (n.d.). *教育雲* [*Learning cloud]*. Ministry of Education. http://learning.cloud.edu.tw/onlinelearning/#

Ministry of Education. (2014). *12-year compulsory education curriculum guideline*. National Academy for Educational Research. https://www.naer.edu.tw/ezfiles/0/1000/attach/87/pta_5320_2729842_56626.pdf

Mullis, I. V. S., Martin, M. O., Foy, P., & Arora, A. (2012). *TIMSS 2011 international results in mathematics*. TIMSS & PIRLS International Study Center, Boston College.

NeuroSky. (n.d.). *Brainwave Sensing Headset*. NeuroSky. https://store.neurosky.com/pages/mindwave

OECD. (2014). *PISA 2012 results: What students know and can do – Student performance in mathematics, reading and science* (Revised ed. Vol. I). PISA, OCED Publishing. https://doi.org/10.1787/9789264208780-en

OECD. (2018). *Equity in education: Breaking down barriers to social mobility*. PISA, OECD Publishing. https://doi.org/10.1787/9789264073234-en.

OECD. (2020). Students' socio-economic status and performance. In *PISA 2018 Results (Volume II)*: *Where All Students Can Succeed* (pp. 49-62). PISA, OECD Publishing. https://doi.org/10.1787/f7986824-en

Paas, F., & Sweller, J. (2014). Implications of cognitive load theory for multimedia learning. In R. E. Mayer (Ed.), *The Cambridge Handbook of Multimedia Learning* (2 ed., pp. 27-42). Cambridge University Press.

Shadiev, R., Huang, Y.-M., & Hwang, J.-P. (2017). Investigating the effectiveness of speech-to-text recognition applications on learning performance, attention, and meditation. *Educational Technology Research & Development, 65*(5), 1239-1261. https://doi.org/10.1007/s11423-017-9516-3

Sun, J. C.-Y., & Yeh, K. P.-C. (2017). The Effects of attention monitoring with EEG biofeedback on university students' attention and self-efficacy: The Case of anti-phishing instructional materials. *Computers & Education, 106*, 73-82. https://doi.org/10.1016/j.compedu.2016.12.003

Sung, Y.-T., Tseng, F.-L., Kuo, N.-P., Chang, T.-Y., & Chiou, J.-M. (2014). Evaluating the effects of programs for reducing achievement gaps: A Case study in Taiwan. *Asia Pacific Education Review, 15*(1), 99-113. https://doi.org/10.1007/s12564-013-9304-7

Terras, M. M., & Ramsay, J. (2015). Massive open online courses (MOOCs): Insights and challenges from a psychological perspective. *British Journal of Educational Technology, 46*(3), 472-487. https://doi.org/10.1111/bjet.12274

World Health Organization. (n.d.). *Coronavirus disease (COVID-19) advice for the public*. World Health Organization. https://www.who.int/emergencies/diseases/novel-coronavirus-2019/advice-for-public

Wu, C.-H., Tzeng, Y.-L., & Huang, Y.-M. (2020). Measuring performance in leaning process of digital game-based learning and static E-learning. *Educational Technology Research and Development, 68*(5), 2215-2237. https://doi.org/10.1007/s11423-020-09765-6

Yang, K.-L., & Lin, F.-L. (2015). The effects of PISA in Taiwan: Contemporary assessment reform. In K. Stacey & R. Turner (Eds.), *Assessing Mathematical Literacy: The PISA Experience* (pp. 261-273). Springer International Publishing. https://doi.org/10.1007/978-3-319-10121-7_14

Yang, X., Lin, L., Wen, Y., Cheng, P.-Y., Yang, X., & An, Y. (2020). Time-compressed audio on attention, meditation, cognitive load, and learning. *Educational Technology & Society, 23*(3), 16-26.