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Do You Think Your Students Are into Online Learning? Brain Responses Using Electroencephalography

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Abstract

The cognitive level of students can reflect the learning performance that results from participation in learning activities in a traditional classroom, which an instructor can support and monitor accordingly. However, it is complicated for online learning. In this study, we used electroencephalography or EEG to investigate students' learning performance for online learning. A cognitive effort index (CEI) application was connected through an EEG headset and used to identify the level of cognitive performance, and a system usability scale (SUS) questionnaire was used to examine student satisfaction. Thirty-six of the students had at least 2 years of experience both on-site and online learning and were enrolled in the controllable instructions: subjects, settings, and durations. The findings of this study surprisingly showed that more than half (22 students) fell into an affective cognitive engagement pattern (AF), 12 students fell into an effective cognitive engagement pattern (EF), and only 2 students indicated a low cognitive pattern. These results showed that most students were significantly attentive to the online activity and only a few students were not able to stay focused during the online activity, in other words, learning in the class online could be as attentive as in the traditional class. The adoption of EEG techniques and EEG interpretation software can reflect awareness and attention in many areas, such as consumer research, consumer behaviors, digital content, and the experience of online education. This study may suggest that Thai business practitioners and marketers adopt EEG to explore consumer behavior.

Keywords: Cognitive; EEG; Brain; Affective Cognitive; Online Instruction

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Introduction

The Coronavirus (Covid-19) pandemic has deeply affected all areas of the globe. Within academia, many universities have been forced to remain closed temporarily. Faced with the difficult situation of how to continue educational programs, academic personnel have been struggling to find solutions to this challenge (Mahapatra, 2020). This new and unusual circumstance calls for online academic institutions to be readily available and functional (Dhawan, 2020). Educational institutions in Thailand have organized online classes to deal with the problems caused by the pandemic, making students unable to study in a traditional classroom. However, most Thai educational content online replicates traditional pedagogy, which consists of an instructor being in front of a camera without having real students. This is a new challenge for the instructor and students in the field of learning effectiveness.

Cognitive load is associated with learning performance. Measurement of cognitive load is important to understand how a learner can learn or memorize it easily and quickly when learning new things, whether it is a study matter or a new skill (Tamanna & Parvez, 2021). The use of psychological knowledge and the neuroscience method enables researchers to study the decision-making process(Alvino et al., 2020); impulsiveness on online trust (Hubert et al., 2018); attention and cognitive skills (Thomas et al., 2013); and engagement and preference (Cha et al., 2020). Normally, the method of monitoring the cognitive process of students during learning takes the form of behavior observation, exams, and quizzes. Unfortunately, in the online learning environment, behavioral observation signals may be difficult to interpret, or are not readily visible, and are not always feasible to monitor (Macaulay & Edmonds, 2004). As a result, educational researchers have begun to use psychophysiological methodology to measure changes in brain activity that occur during the learning process via electroencephalography or EEG (Etnier et al., 1996). Using psychophysiological methodology to measure changes in brain activity, it allows researchers the opportunity to make previously invisible thinking processes observable (Gere & Jauscvec, 1999).

Electroencephalography (EEG) devices have been widely used in medical and health research and are currently being used in educational research to improve student performance. Previous studies have used a portable EEG headset to assess the cognitive state of students as they perform learning tasks; (Chen et al., 2017; Chen & Lin, 2016; Xu & Zhong, 2018) used an EEG headset to measure student learning performance by evaluating their level of attention from the headset. An EEG device can automatically measure the participant's attention, emotion, and meditation levels in real time. It can be considered one of the important contributions to research in online education. The researcher suggests that the use of EEG in real-time cognitive monitoring can improve student learning effectiveness.

Different techniques are available to measure cognition. Most studies used subjective rating scales to assess cognitive load (Paas et al., 1994), task-invoked pupillary response (Skulmowski & Rey, 2017), EEG signals (Antonenko et al., 2010), fMRI, etc. In Thailand, studies of cognitive performance were measured with EEG in ADHD (Siripornpanich, 2013) as well with Thai elderly people (Israsena et al., 2021; Tantisatirapong et al., 2021). However, there have been no studies in Thailand that have used EEG to measure cognitive performance with adolescents in online education. Furthermore, the cognitive effort index (CEI) is a new technique that combines neuroscience, particularly EEG, and cognitive measurement that focuses on attention developed by Gvion and Shahaf (2021). Therefore, this study aims to use the cognitive effort index (CEI) application and EEG device to measure student cognition when learning in an online class. The research questions are as follows:

1) Does online learning affect student cognition?
2) Are students satisfied with using an EEG device to measure cognitive levels during online learning?

Literature Review

Online Instruction

Most universities and colleges offer online instruction as an optional activity that every university should do. Allen and Seaman (2010) showed that approximately 30% of university and college students in the United States take at least one online course class. However, online courses have limited interaction with the instructor. Limited interaction may in turn decrease the satisfaction with the student's course and affect their performance (Cheng et al., 2019; Noel-Levitz, 2011). Online instruction requires that a student is confident in performing Internet-related actions and willing and able to self-manage the learning process (Sun & Rueda, 2012). A student with low confidence in the use of the Internet may be less engaged in the learning activities and have fewer opportunities to interact with the instructor or classmates, thus leading to dissatisfaction with online learning (Liang & Tsai, 2008). Several studies show that students have distractive multitasking behaviors when accessing a laptop in the classroom, which is associated with a decrease in performance (Junco & Cotten, 2011;Wood et al., 2012).

Electroencephalography (EEG) and Application of EEG

An EEG device is a method to record the electrical activities of the brain. EEG devices and EEG application transfer EEG data from mental states to computers wirelessly or via Bluetooth. Previous studies have demonstrated five categories of EEG data applications; brain-computer interfaces, biometrics, custom solutions, neuroscience and clinical applications, and neuromarketing (Soufineyestani et al., 2020). Brain-computer interfaces are one of the most common applications of EEG and use real-time EEG data to help people with disabilities or motor activity impairment (Guger et al., 2017). For example, Campbell et al. (2010) used EGG to record the activities in the study of controlling mobile phone applications using eyewinks. Moreover, Hawsawi and Semwal (2014) studied body gesture and eye movement to control a video game using EGG, and Alomari et al. (2014) studied mouse control using imagined hand movement and EGG. Neuroscience research also used an EEG headset and EEG application to understand the functionality of the nervous system (Soufineyestani et al., 2020). The researchers are now able to understand how humans experience different emotional states and how their brains work in various mental states via an EEG headset and its application (Soufineyestani et al., 2020).

The advantage of using EEG for educational research is that it can detect brain participation and show how brain activity changes while the mind is engaged in cognitive tasks (Antonenko et al., 2010). Previous studies have used EEG devices as a tool for improving education research which include: Chen-Huei (2017), who used an EEG to examine the differences between game-based learning (GBL) and traditional learning. Additionally, Chen and Huang (2014) developed the Attention-Based Self-regulated Learning Mechanism (ASRLM). ASRLM uses brainwave detection and was designed to enhance the sustained attention of learners while engaged in a reading task. Chen and Wu (2015) explored how three commonly used video lecture styles influenced sustained attention, emotion, cognitive load, and the learning performance of participants. Sun and Yeh (2017) explored the potential benefits of using EEG by providing audio feedback based on individual brain wave signals during learning tasks.

Cognitive Load Theory

Cognitive Load Theory (CLT) is an instructional design based on a human cognitive architecture that explains a working memory limited in capacity and a long-term memory unlimited (Antonenko et al., 2010; Sweller, 1988). Cognitive load (CL) has been subcategorized into intrinsic cognitive load, extraneous cognitive load, and germane cognitive load (Kruger et al., 2014). The intrinsic cognitive load is an inherent quality of the material that is difficult for the participants. Intrinsic cognitive load can be measured from the complexity of the instruction material (Kumar & Kumar, 2016). An extraneous cognitive load is created by the way that material is presented to the learner (Kruger et al., 2014; Kumar & Kumar, 2016). Germane cognitive load is the result of an innovative approach to manipulating information in a way that is conducive to learning (Sweller et al., 2010). Cognitive load can be used to measure aspects of interactions that may lead to increased difficulty in the context of human-computer interaction (HCI) (Kumar & Kumar, 2016).

Measurement of Cognitive Load Using EEG

The EEG device is a neurotechnology that measures electrical activity in the brain through portable devices that are placed on the scalp. The EEG signals produced by the brain are rhythmic and can be described in frequency bands. The five basic frequency bands are delta, theta, alpha, beta, and gamma. Each frequency is associated with a mental state (see Table 1). Alpha and theta have been reported to be sensitive to the difficulty of task manipulation (Kruger et al., 2014). According to (Antonenko et al., 2010) indicated that alpha and theta rhythms are related to task difficulty or cognitive load in a variety of task activities. The measurement of brain waves in the alpha and theta brain wave frequencies reflects what is happening in the learner's information processing situation. EEG can predict cognitive levels from the learner's response, making EEG an appropriate choice to assess cognitive load in educational psychology (Antonenko et al., 2010).

Table 1: Five Frequency Bands Associated with Mental States.

Band Name	Frequency	Mental State
Delta	0-4 Hz	Deep sleep, unconscious
Theta	4-8 Hz	Creativity, dream sleep, drifting thoughts
Alpha	8-12 Hz	Relaxation, calmness, abstract thinking
Low Beta	12-15 Hz	Relaxed focus, integrated
Midrange Beta	15-20 Hz	Thinking, aware of self, high alertness
High Beta	21-30 Hz	Alertness, agitation
Gamma	30-100Hz	Motor functions, higher mental activity

Cognitive Effort Index (CEI)

The cognitive activity index is an innovative technique that provides a measure of cognitive workload based on psychophysiological objectives. This research used the cognitive effort index (CEI) application developed by Gvion and Shahaf (2021) to measure the levels of cognitive workload through an EEG device. The application analyzed the dynamics of the cognitive index and created three patterns (see Figure 1).

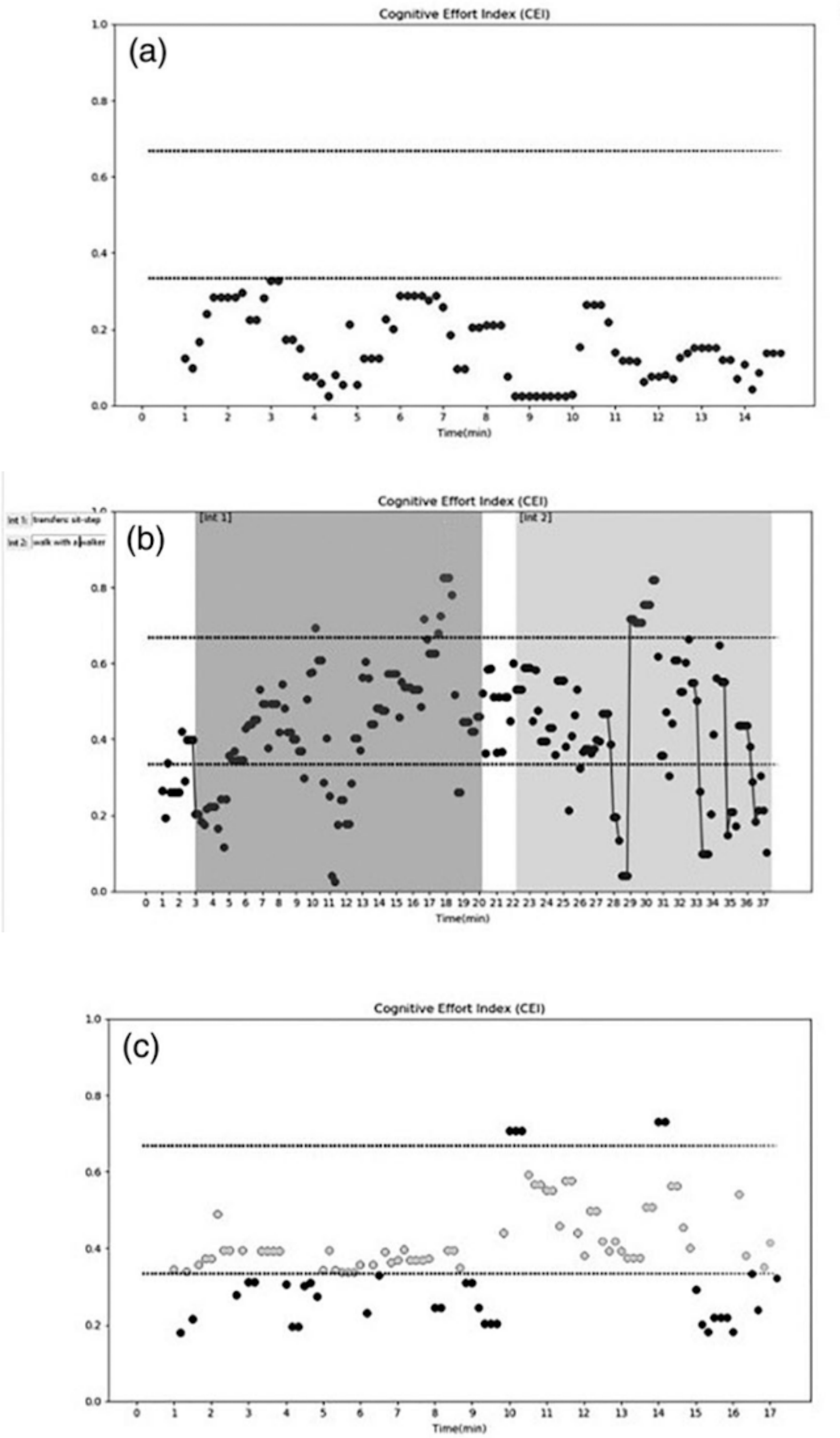

Figure 1: Three Cognitive Patterns (Gvion & Shahaf, 2021). a) A Low Cognitive Engagement Pattern, b) An Affective Cognitive Engagement Pattern and c) An Affective Cognitive Engagement Pattern.

Gvion and Shahaf (2021) described the patterns of the cognitive effort index (CEI) marker dynamics in their software as follows.

a) A low cognitive engagement pattern is a pattern consistent with a cognitive barrier to participation meaning that the user/learner has some difficulties focusing on the activity or task.
b) An affective cognitive engagement pattern is a pattern that shows sharp decreases and sharp increases representing distraction induced by the stressor and reduced attention to the ongoing exercise meaning that the user/learner has some anxiety and high attention interchangeably on the activity or task.
c) An effective cognitive engagement pattern is a pattern in which most points are consistently in the middle range meaning that the user/learner has a steadily good level of engagement.

Several studies have used other tools to measure cognitive workload. Marshall (2002) used the Index of Cognitive Activity (ICA) as a technique to estimate the levels of cognitive effort of the users. The ICA application was developed to measure cognitive performance based on changes in pupil dilation with visual display. However, in this study, it was difficult to measure pupil changes on complex tasks, especially in online activity. On the other hand, the CEI application was developed by as an easy-to-use application to monitor the participants' attentive engagement in real-time. Furthermore, the EEG headset provided accurate attention values and was comfortable to wear (Kuo et al., 2017).

Research Methodology

Participants

In total, 36 subjects were in their early twenties (24 females; 12 males) with no record of neurological disease and normal vision. The researcher used a convenience sample of participants by recruiting 3 6 volunteers from undergraduate students in Mahasarakham, Thailand. Prospective study participants are recruited based on their determination to start online learning courses. The University Institutional Ethics Review Board (ERB) issued its ethical approval, and informed consent was obtained from all volunteers. In general, the number of subjects in neuro studies is very limited because of the high cost and time involved. For example, Ruanguttamanun (2014) used data from one subject using fMRI in a high-end product study, Hubert et al. (2018) used 20 participants in an fMRI study to evaluate trustworthiness in an online setting, and Alvino et al. (2020) recruited 26 participants in a wine tasting experience using EEG measurement.

EEG device and cognitive effort index (CEI)

The NeuroSky Mindwave headset and the CEI application were used to analyze the level of cognitive engagement. The Mindwave is a portable headset with a single EEG sensor. The sensor can measure the electrical activity in the brain, including alpha and theta waves. Previous studies by Ni et al. (2020) reported that Mindwave had satisfactory validity and reliability to measure the brainwave of learners in learning activities. Several developers have developed applications for users to monitor and report the brain wave signal connected via Mindwave including the CEI.

The system usability scale (SUS) questionnaire

User interaction satisfaction was important in the learning process because a smooth experience positively affected satisfaction (Guo et al., 2007). Tsai et al. (2011) found that online learning dissatisfaction was caused by learners' low engagement in online learning activities that tended to have fewer opportunities to interact with the instructor or classmates. The system usability scale (SUS) questionnaire was used to determine whether the satisfaction scores were significantly equal to or greater than the mean SUS score of 68 (Sauro & Lewis, 2011). The SUS score presented the usability performance with respect to effectiveness, efficiency, and overall ease of use. The average SUS score falls to the 50th percentile. Based on 500 studies using SUS scale, the average score was 68, with an SUS score above 68 considered above average, and anything below 68 considered below average (Sauro & Lewis, 2011).

Procedures

This study was conducted to determine the effectiveness and ease of using an EEG headset to assist in an online course. First, participants were asked to come to a normal classroom on site at Mahasarakham University and sign an informed consent form. The participants were then informed of the detailed instructions verbally before participating in the experiment in the online class. The study was carried out one at a time, as there was only one EEG headset. Once the participant sat in the chair, the researcher asked each of them to relax while putting on the headset. The participant was also asked not to move suddenly while watching the e-Commerce lesson on the computer screen. All participants were sophomore in Business Computer Major and were classmates who shared the same learning level. This study did not focus on what they could learn from the lesson, instead, it measured attention and satisfaction of the online experience. The experiment took approximately 30 minutes to complete. At the end of the session, the headset was removed and the SUS questionnaire was handed to the participant. Figure 2 shows a graphical representation of the research procedures.

Figure 2: Research Procedures Overview.

Data Collection

CEI was an indicator of the interpretation of the brain wave, which was reported in three patterns: Affective cognitive engagement pattern (AF), Effective cognitive engagement pattern (EF) and Low cognitive engagement pattern. Therefore, the SUS questionnaires were used to evaluate the use of the EGG headset and to determine whether the participant was satisfied with the selected tool or not. If the results were greater than 68, it would be considered above average.

Research Findings

Cognitive Results

The patterns in the cognitive effort index (CEI) consist of the affective cognitive engagement pattern (AF), the effective cognitive engagement pattern (EF), and the low cognitive engagement pattern. The result of the cognitive effort index (CEI) shows that the online class had a positive effect on the cognitive level; 22 and 12 students indicated the affective cognitive engagement pattern (AF) and the effective cognitive engagement pattern (EF), respectively. To answer the first research question, (Does online learning impact student cognition?) only two students resulted in a lack of engagement or represented low cognitive engagement patterns, which was an unexpected result. This finding indicated that only two students were consistent with a cognitive barrier to engage, whilst 22 students showed their attention or focus in the middle range meaning that they could engage but were not as focused as those 12 students who represented a higher level of attention.

SUS Results

The SUS results indicate that the students were satisfied with the experience of using the EEG headset. According to the average SUS score, the number that is equal to or greater than the mean SUS score of 68 indicated participant satisfaction (Sauro & Lewis, 2011). Thus, the average score of 69 in this study implies that the students were satisfied with using the EEG in the online class. See Figure 3 for the graphical representation of the cognitive comparison of the students with the CEI pattern.

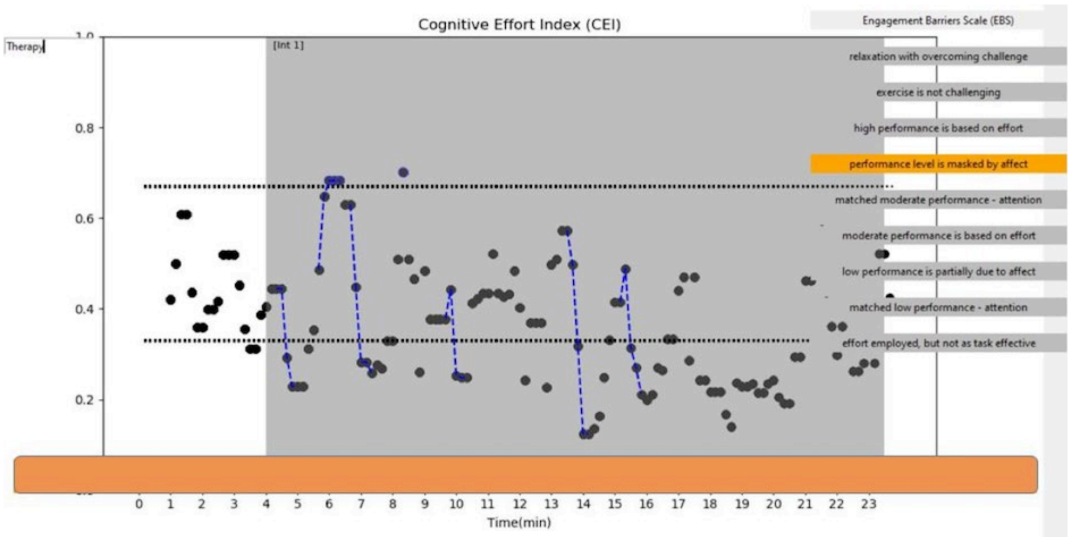

Figure 3: Effective Cognitive Engagement Pattern from CEI Manual. The Application Generated The Pattern and Its Results on The Right Bar.

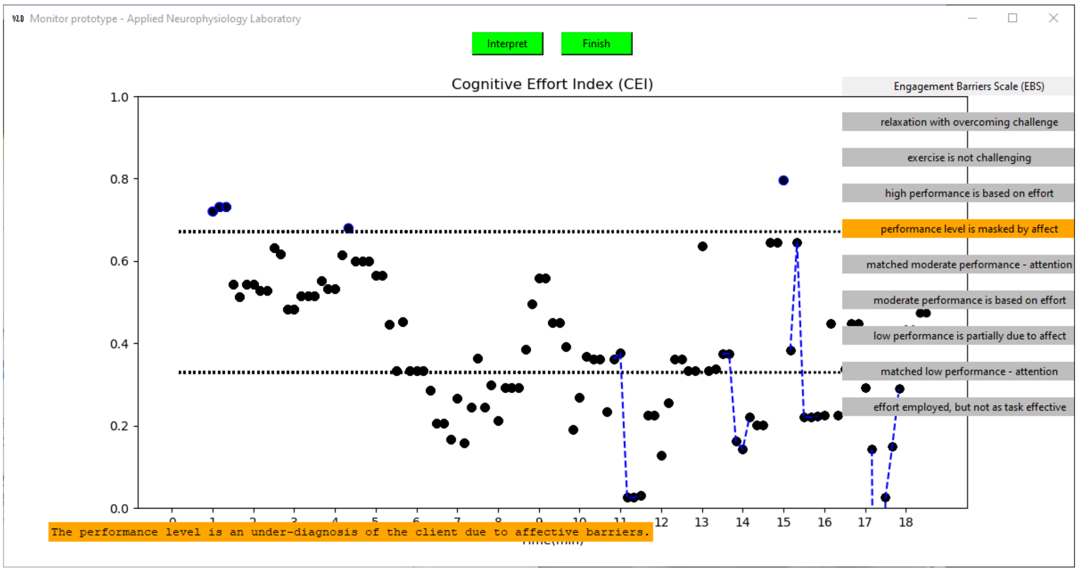

Figure 4: The Pattern of an Effective Cognitive Engagement was Generated in The Right Bar That Performance Level was Marked by "Affect".

Discussion

Theoretical Contributions

This study offers several contributions to the related literature. First, the findings contribute to our understanding of how to measure the level of cognition in real time. Cognitive load theory was used to explain student cognition through the cognitive effort index (CEI) application and an EEG device. The cognitive effort index (CEI) application analyzed the cognitive of the students in three patterns: affective cognitive engagement pattern (AF), effective cognitive engagement pattern (EF), and low cognitive pattern. The CEI application and an EEG device help analyze the findings of this study. Gvion and Shahaf (2021) confirmed that the CEI application was used appropriately to monitor barriers of patient participation for improved rehabilitation. An additional contribution of this study is the use of EEG device to conduct the research in an online setting. Student satisfaction was examined by using the system usability scale (SUS) questionnaire to determine how satisfied the student was while using the EEG device. There were two specific questions asked regarding the use of an EEG headset to measure cognitive and satisfaction with the new technology that monitors cognition without an instructor.

For the first research question (Does online learning affect student condition?) the answer to the research question is that online learning did not influence student engagement. There were 36 students who participated in the experiment. The results showed that more than half (22 students) fell into an affective cognitive engagement pattern (AF), 12 students fell into an effective cognitive engagement pattern (EF), and only 2 students indicated a low cognitive pattern. The affective cognitive engagement (AF) is that students can focus on learning task but not as focused as the effective cognitive engagement (EF). A low cognitive pattern means that the student cannot focus on the learning task.

The EEG headset and the CEI application might have increased the awareness of the students about the experiments and a reflection of their mental states, similar to the Hawthorn effect when participants were told to participate in the experiments. For the second research question (Are students satisfied with using an EEG device to measure cognitive levels during online learning?) the results showed that the students were satisfied. The range score was between 53 and 83, with an average of 69.

The cognitive effort index (CEI) is an innovative technique that provides an important estimate of the levels of cognition of the students. The EEG headset and the SUS score could be combined to measure student attention, which leads to performance in online classes without an instructor monitor. The findings of this study imply that we have an easy-to-use tool to measure cognition. In other words, the instructor should provide more support to students to achieve higher test scores in high-difficulty courses.

Practical Contributions

The practical contribution of this study is knowledge for the field of neuroscience. In addition, an EEG device is becoming more mature and affordable to use and can automatically measure participant attention and meditation levels in real-time (Xu & Zhong, 2018). This study provided a way how for business professionals, decision-makers, and researchers to analyze attention and emotional aspects of consumer experience and neuroscience research. Ariely and Berns (2010) presented that business can use EEG technology to develop marketing strategies. The researcher showed that the EEG device and software could measure the decision to buy choose products.

Another practical contribution is the application for analyzing the brain signals. Most of the applications are free and easy to use with an EEG device. This study used the NeuroSky Mindwave, which was developed at low cost with a sensor that can measure the level of attention while being used as a normal headset. Previous studies confirmed that NeruoSky was a positive correlation between measured and self-reported attention levels (Kuo et al., 2017). Sun (2014) used this device to monitor students' brainwave activity, and Chen and Hung (2014) also used NeuroSky to investigate students' sustained attention. This study offers how to use an EEG device and an EEG application to measure the level of cognition and attention. It may lead researchers and professionals into the field of neuroscience.

Implications and Conclusions

Before the 2019 pandemic, the Thai educational environment was not prepared for an online classes, as the necessary technology was not in place to enable the system. During the pandemic, all schools have had to implement online classrooms without the quality and efficiency of technology. According to the Suan Dusit Rajabhat University survey, a large majority of people think online learning will worsens the quality of Thai education. 66.16% of parents and guardians surveyed were worried that children could not concentrate on learning and lack enthusiasm, while 64.64% were worried that children could not fully understand the lessons (Bangkok Post Online, 2021). In contrast, the first research question of this study is "Does online learning affect student cognition?" The EEG results of this study show that students are significantly attentive during online instruction. Hence, using EEG to measure cognitive capability could expand into a wider area of online classes, such as the quality of digital content and online education experience.

In terms of business implications, applications of EEG to consumer neuroscience research have been widely used in developed countries due to affordability, portability, and ease of use, but the application of EEG research in Thailand is found primarily in clinical trials.

The adoption of EEG techniques and their interpretation software is widely recognized as a method that can reflect awareness and attentiveness in consumer research. This study may suggest that Thai business practitioners and marketers adopt electroencephalography (EEG) to explore consumer behaviors, as it is one of the most commonly applied neuroscientific techniques for marketing studies (Bazzani et al., 2020).

Student satisfaction is an important indicator of programs or courses that reflect the positive aspects of their learning experiences. Previous studies show that high student satisfaction can lead to lower dropout rates and it is associated with program quality and student success in program evaluation (Kuo et al., 2014). The second research question is "Are students satisfied with using an EEG device to measure cognitive levels during online learning?". For the answer, this study used the system usability scale (SUS) to investigate student satisfaction. The finding of this study indicated that the EEG headset could be used to monitor the cognition of participants during online activity because the SUS score average is higher than 68, which means that most students are satisfied. However, several studies argued that the participant feels distraction and discomfort when wearing the EEG (Mampusti et al., 2011; Suttidee, 2020). These issues need to be considered and improved in future research.

Limitations and Future Research

This study has several limitations that need to be addressed. First, the participants in this study came from only one university; the results may not generalize well to other settings. The sample is Thai-focused, with 100% of the respondents residing in Northeast Thailand, which is considered the poorest, and they are keen to learn new things involving new technologies. This could be another bias in the satisfaction results. Second, this study used only one lesson with the same difficulty level for all participants. Future research is needed to determine more details, such as the difficulty levels of online instruction, the types of courses, and the graphics or media used. Furthermore, the research environment of this study was held in a physical school, which did not give participants a real feeling of being home for online sessions. A final limitation was the EEG headset itself. Although the headset was easy to place on the heads of the participants, the device can be minimally adjusted, which can cause the results to alter accordingly since the EEG sensor must be in good contact with the forehead. Future research may use more sensors that can measure other behaviors, for example, emotion, meditation, etc. The eye tracking and EEG headset could be considered to be used together for analysis of various cognition in business practices. Further research areas, including consumer profiling and social consumer neuroscience, have not yet been sufficiently explored and would benefit from EEG techniques to address unanswered questions.

Data Availability

Data are available via e-mail at chutima.r@acc.msu.ac.th

Conflicts of Interest

The authors declare no conflicts of interest.

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