Effects of Audio and Tactile Biofeedback Based on EEG Attention Levels on University Students' Relaxation

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Abstract: This study aims to examine the effects of audio and tactile biofeedback based on EEG attention levels in anti-phishing education on university students' relaxation. The study developed an attention feedback system to provide learners with audio and tactile biofeedback by collecting learners' EEG attention signals and converting them to attention levels. The research method employed a quasi-experimental design. The participants were 90 university students who had no prior anti-phishing learning experiences. A random grouping was adopted to divide the participants into a non-immediate feedback group, an audio-immediate feedback group, and a tactile-immediate feedback group. Each participant was required to wear a portable EEG device that was connected to an attentional feedback system to collect their EEG attention and relaxation signals during the learning activity. After the learning activity, participants were asked to complete a post-activity feedback questionnaire. The results showed that the tactile-immediate feedback group displayed a significantly higher level of relaxation as compared to the audio-immediate feedback group. The study suggests that instructors may consider using tactile-immediate biofeedback based on learners' attention levels to help regulate attention and improve relaxation in online learning environments.

Keywords: Audio and tactile feedback, EEG biofeedback, relaxation, anti-phishing

1. Introduction

Remote online learning became a new norm in education after the COVID-19 pandemic in March 2020. The impact has silently revolutionized the education system to embrace technology-based cloud learning. However, this brings some challenges. According to the trends report from the Anti-Phishing Working Group (APWG), there was a sudden increase in phishing attacks against videoconferencing service provider Zoom (APWG, 2020) where schools worldwide were switching to video conferencing for their remote learning. Another survey from the 2020 Cyber Threats Report (Netwrix, 2020) stated that 33% of educational organizations felt they were at greater cybersecurity risk than pre-pandemic, 89% of them found new security gaps caused by the rapid transition to remote learning, and 50% of educational organizations had experienced phishing attacks. Today, there is growing concern about VPN exploitation and credential stuffing compared to pre-pandemic when malware or phishing was a major concern. Growing demand for cybersecurity awareness training will become an important trend in K-12 schools and higher education institutions.

Previous studies showed that effective anti-phishing education is the key to preventing phishing attacks (Sun et al., 2016). However, many of the anti-phishing materials highly rely on students' self-learning. The complex digital worlds and other environmental distractions are competing with human's limited attentional resources and increasing stress. To make self-learning effective, educational psychologists should accelerate the research on innovative

approaches to assist students' self-regulation of attention and motivation, as well as managing stress in the midst of learning remotely and individually.
A branch of brain-computer interface (BCI) study has emerged that focuses on designing attention-aware systems that assist users in effectively allocating their attentional focus to optimize engagement (Vertegaal et al., 2006). Since the 1970s, BCI has been actively employed as an assistive technology for clinical or therapeutic purposes, and has been applied to "locked-in" patients or children with attention-deficit/hyperactive disorder (ADHD). In recent decades, the development of Electroencephalography (EEG) and the advances in computing power have provided a cost-efficient, safe, and portable approach which not only allows the use of EEG data to understand users' cognitive states, but also serves as immediate communication with adaptive interfaces of visual, audio, or tactile feedback to influence and augment cognitive functions (Tan & Nijholt, 2010; Vasiljevic & Miranda, 2023). Sun and Yeh (2017) used audio biofeedback based on EEG attention signals to improve learners' attention, and showed that it was an effective strategy. The EEG biofeedback can help learners quickly achieve deep relaxation (Rydzik et al., 2023). Xu and Zhong (2018) showed that when learners' attention and relaxation levels are high, this state of mind can help them learn better. Relaxation, also known as meditation (Xu & Zhong, 2018), can also reduce anxiety (Hardt, 2012). Holmes (2019) suggested that understanding how to integrate neuroscience and mindfulness education to train self-regulation and match learners' learning requirements is an important issue. Therefore, the issue of how to balance attention and relaxation in the learning process needs to be explored. Previous studies indicated that tactile feedback can improve novices' relaxation in a digital environment, and does not affect attention (Kim et al., 2021) or the performance of visual tasks (Alahakone & Senanayake, 2010). This study aimed to develop an attentional feedback system that provides audio and tactile biofeedback based on EEG attention levels to create a personalized learning environment. The study also examined the effect of audio and tactile biofeedback on university students' relaxation levels. The following research question was addressed in this study and the research model is shown in Figure 1.

Research question: Are there significant differences in relaxation among university students using non-immediate, audio-immediate, and tactile-immediate feedback based on EEG attention levels in online anti-phishing education?

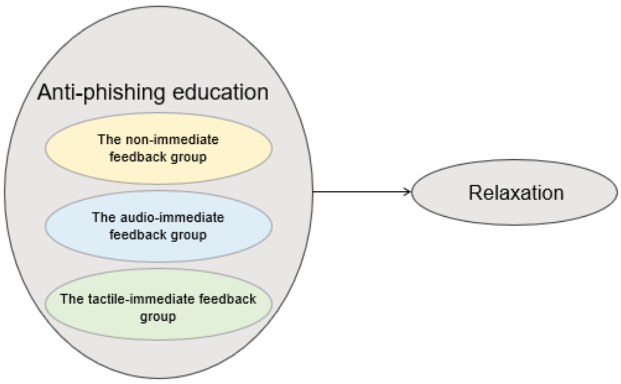

Figure 1. The research model

2. Method

2.1 Participants

The study participants were 90 university students from Taiwan, excluding those who had prior learning experience of anti-phishing. The effective sample comprised 90 (100%) students. The participants were randomly divided into three groups: a non-immediate feedback group (n = 30), an audio-immediate feedback group (n = 30), and a tactile-immediate feedback group (n = 30). There were 36 males (40%) and 54 females (60%), with an average age of 22.7 years and a standard deviation of 2.83. In terms of academic areas, 23 participants were from the College of Humanities and Social Sciences (25.56%), 13 were from the College of Electrical Engineering (14.44%), 11 were from the College of Engineering (12.22%), 10 were from the College of Information Science and Technology (11.11%), 10 were from the College of Management (11.11%), nine were from the College of Science (10.00%), and 14 participants were from other colleges (15.56%).

2.2 Experimental procedure

The informed consent process included the researcher explaining the content of the consent form to the participants before the experiment. After the participants understood the content, they voluntarily agreed and signed the consent form. Before starting the experiment, participants needed to put on the portable EEG device for approximately one minute and confirm that it did not make them uncomfortable. In the next step, researchers took the portable EEG paired with the attentional feedback system and tested the biofeedback for approximately two minutes. When the attentional feedback system was completely prepared, participants could start the online anti-phishing learning activity. The learning activity lasted approximately 30 minutes. The EEG attention and relaxation signals were recorded during the learning activity for the three groups. The non-immediate feedback group did not receive any sensory feedback based on their mental attention states. The audio-immediate feedback group received audio biofeedback when their attention level fell below the threshold of focused attention state. The tactile-immediate feedback group received tactile biofeedback when their attention level fell below the threshold of focused attention state. After the learning activity, participants were asked to complete a post-activity feedback questionnaire, which took approximately 10 minutes. The experimental flowchart is shown in Figure 2.

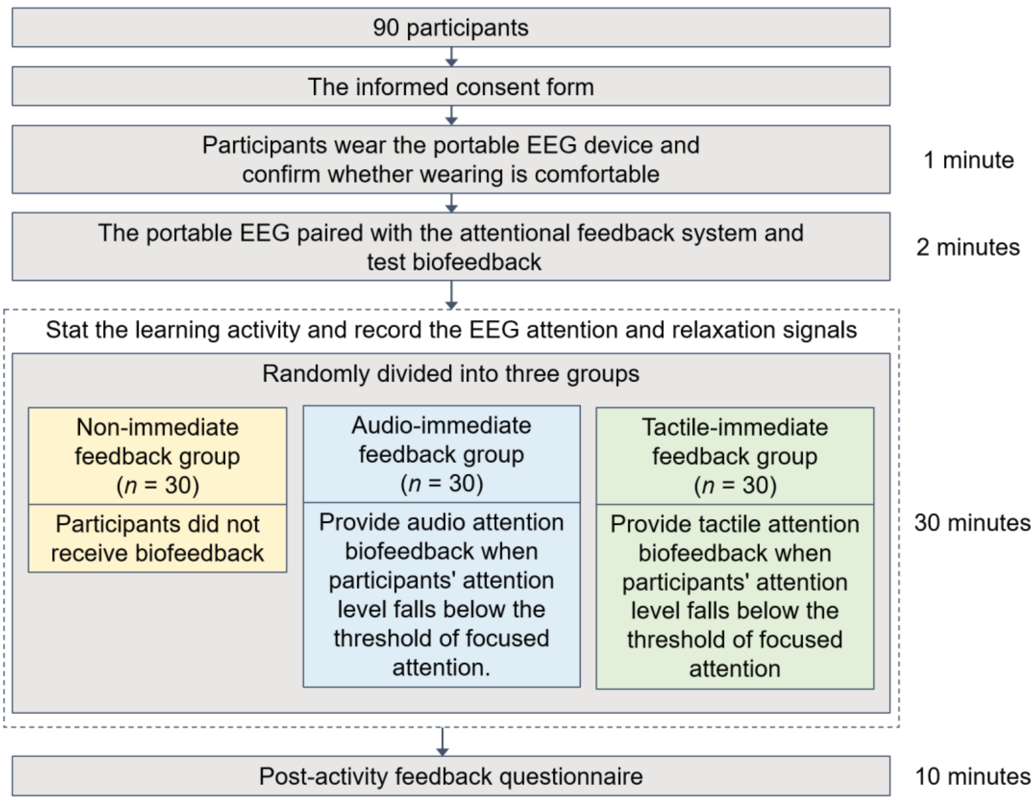

Figure 2. The experimental flowchart

2.3 Instrument

2.3.1 The attentional feedback system

The attentional feedback system was designed and planned by researchers and developed by a technology company. This system was a mobile application based on Android development platforms, and the mobile device used in this study was a Samsung Galaxy S8 smartphone. The attentional feedback system was connected to the portable EEG device by Bluetooth to collect EEG attention and relaxation signals. It provided attention biofeedback based on learners' attention levels. The attention levels were calculated by the eSense algorithm and the ThinkGear chip from NuroSky (2017). The ThinkGear chip enhanced the raw EEG signals and filtered noise and muscle movement interference. The eSense algorithm converted the raw EEG values into relative attention levels ranging from 0 to 100 to describe the range of brain activity. Besides 0 meaning the signals were unable to be used, other scores were divided into five ranges to determine the attention levels: 1 to 20 indicated strongly lowered levels, 20 to 40 indicated reduced levels, 40 to 60 indicated neutral levels that were similar to the baseline, 60-80 indicated slightly elevated levels, and 80 to 100 indicated elevated levels. In this study, the biofeedback triggered audio or tactile feedback when the attention scores were below 40 and lasted for more than seven seconds. The system controlled the interval between two instances of feedback for at least 30 seconds. This study also used this system to collect relaxation signals and used the same method to estimate the relaxation levels. The user interface and design of audio and tactile biofeedback are shown in Figure 3.

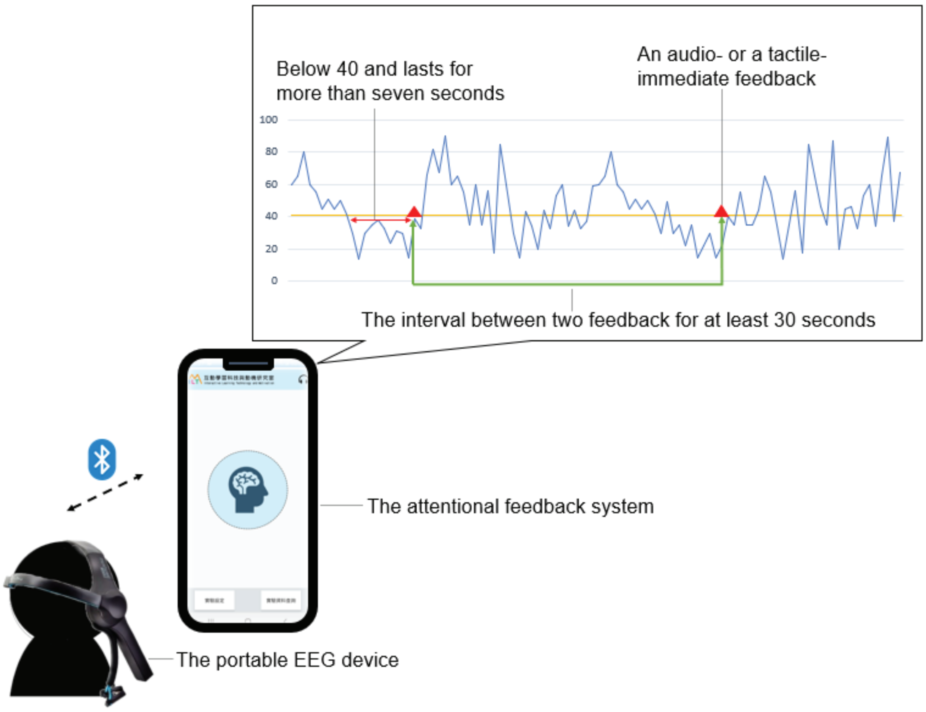

Figure 3. The design of audio and tactile biofeedback

2.3.2 The post-activity feedback questionnaire

The post-activity feedback questionnaire was modified from Sun and Yeh (2017). The questionnaire includes three issues: use experience, timing and perception of receiving attention feedback, and other perceptions. It aimed to understand learners' perceptions of using the attentional feedback system, and collected their suggestions to improve the design of the learning activity and the biofeedback system in the future. The non-immediate feedback group had five items in their questionnaire, whereas both experimental groups, the audio-immediate feedback and the tactile-immediate feedback group, had eight items respectively.

3. Results

This study used the analysis of variance (ANOVA) to analyze the results by the IBM SPSS Statistic 25 software. The sample conformed to the normal distributions based on the criterion of Kline (2011) and did not reject the hypothesis of the equality of variances by Levene's test ($F(2,87) = 1.07$, $p = .35$). According to Table 1, the ANOVA results indicated that the relaxation levels were significantly different among the three groups ($F = 3.70$, $p < .05$, $\eta^2 = .08$). Because the sample sizes of each group were equal, we chose Tukey's HSD test to analyze the post-hoc comparisons. The results of Tukey's HSD's post-hoc comparison show that the relaxation level of the tactile immediate feedback group ($M = 40.72$, $SD = 16.61$) was significantly higher than that of the audio immediate feedback group ($M = 30.41$, $SD = 13.70$), indicating that learners who used tactile biofeedback based on EEG attention levels could improve their relaxation levels compared to audio biofeedback. Table 1 shows the descriptive statistics for relaxation and Table 2 shows a summary of ANOVA for relaxation for the three feedback groups.

Table 1. *Descriptive statistics for relaxation*

Group	*M*	*SD*	skewness	kurtosis
Non-immediate feedback group (*n* = 30)	38.77	16.27	-0.03	-1.02
Audio-immediate feedback group (*n* = 30)	30.41	13.70	0.94	0.90
Tactile-immediate feedback group (*n* = 30)	40.72	16.61	0.35	-0.54

Table 2. *A summary of ANOVA for relaxation*

Source of variation	*SS*	*df*	*MS*	*F*	*p*	η^2	*Post hoc*
Between-group	1798.31	2	899.16	3.70	< .05	.08	(C) > (B)
Within-group	21122.87	87	242.78				
Total	22920.18	89					

Note. (A) indicates the non-immediate feedback group; (B) indicates the audio-immediate feedback group; (C) indicates the tactile-immediate feedback group

4. Discussion and conclusion

According to the results, the relaxation levels were significantly different among the three feedback groups, with the tactile-immediate feedback group displaying higher levels of relaxation as compared to the audio-immediate feedback group. Relaxation can reduce anxiety (Hardt, 2012) and stress, and improve learners' learning process (Holmes, 2019). Therefore, tactile biofeedback was a helpful strategy to remind learners to focus their attention levels without increasing their anxiety or stress, as a higher relaxation level resulted. Additionally, tactile-immediate feedback helps learners regulate their behavior and avoid competing with visual tasks (Alahakone & Senanayake, 2010). The result is also consistent with Kim et al. (2021), who found that tactile feedback can help people adjust their breathing to improve attention, while audio feedback interferes with attention. Participants' written feedback aligned with the findings. Examples are: “When the smartphone vibrates, it reminds me to focus on the content on the screen” (Tactile 27); “When the vibration occurs, I will recall my status of attention” (Tactile 10); “The sound playing may startle and cause distraction” (Audio 29); and “The sound is very harsh” (Audio 28). Therefore, this study suggests that instructors can use tactile feedback based on learners' EEG attention levels to enhance their relaxation levels. Future research can extend to examining learners’ preferences for volume and melody, negative reinforcement issues, and different tactile patterns.

Acknowledgements

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