Differences in EEG Activity According to Online Learning Content Types

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This study explores how the effects of learning vary according to the online learning content type from a neurological perspective by analyzing the change in EEG activity from the frontal lobes of the brain of college students according to the online learning content type. The four types of online learning content are instructor-centered, instructor-text-centered, text-centered, and video-centered. The conclusions obtained based on the results of this study are as follows. The instructor-text-centered type showed the highest levels of beta waves and gamma waves. This is a characteristic of cognitive activity that involves working memory during learning. In other words, this type is the most suited to online learning. This study is meaningful in that it provides further empirical results on the types of online learning content during the online learning process by focusing on the learner's cognitive activity from the perspective of neuroscience by integrating EEG activity and pedagogy.

Keywords: Online Learning, Online Learning Content Types, EEG, Brain wave

Introduction

The COVID-19 pandemic has completely changed the present state of education and its future. Universities in South Korea also introduced full online classes to ensure continued academic learning for students amid long-term social distancing (Ministry of Education, March 2, 2020; OECD, 2020). Until now, online learning at universities in South Korea has been used as an auxiliary means of face-to-face classes or to supplement institutional education. Before the full-scale implementation of online learning due to the pandemic, the percentage of online learning in universities in South Korea stood at 1%, and 0.9% in technical colleges (Jung, B. Y. et al., 2020; Korea Council of Private University Presidents, 2020. 3. 16.).

As of 2022, university classes are being conducted both online and offline, rather than seeing a complete return to the in-person classes of the past. In particular, some liberal arts and required courses are still being operated in a contact-free setting using online learning content. Therefore, a systematic approach to online learning is required from the point of view of preparing for future education by utilizing the abundant data and operating experiences obtained from online learning that began in the wake of COVID-19 (Kim, H. J., 2020b). In addition, systematic research for more effective online learning management is continually needed in light of new pandemics due to infectious diseases or other obstacles to attending school in person (Hong, S. V., & Yoo, Y. J., 2020).

The Ministry of Education of South Korea presented online learning operating standards consisting of synchronous online learning and asynchronous online learning to systematize learning in online learning situations after COVID-19 (Ministry of Education, March 27, 2020). The Ministry of Education recommended synchronous online learning for smoother interaction in contact-free classes, but as a result of online learning programs, the proportion of teachers, who operated synchronous online learning programs using online learning content, accounted for the largest portion (Jung B. Y. et al., 2020). Looking at the online learning operation cases of universities, 50.2% of professors operated asynchronous online learning classes, and 24.8% of professors conducted synchronous online learning classes. It was confirmed that 21.8% of professors conducted online learning classes by combining two or more methods, such as synchronous online learning and synchronous online learning (Ministry of Education, September 9, 2020). If classes continue in contact-free environments in the future, most professors predicted that asynchronous distance classes using online learning content would be conducted rather than synchronous online learning methods (Lee, S. C. et al., 2020).

The reason that instructors create and use their own online learning content is because existing online learning content produced by educational institutions such as the Educational Broadcasting System (EBS) and the Korea Education and Research Information Service (KERIS) differ from the instructor's curriculums (Kim, H. J., 2021). In addition, asynchronous online learning programs using online learning content have the advantage of allowing learners to participate in classes flexibly, at any time, and in any place, since they are not limited by time and space, and learners can repeat their lessons according to individual learning speeds (Kim, J. W., Park, Y. S., Yang, G. S., 2021; Lee, Y. S., & Shin, D. K., 2020).

However, in a class using online learning content, the instructor records the class in advance, and the content is delivered through video, so the instructor cannot intervene during the class directly. In other words, classes using online learning content can cause cognitive overload depending on the instructional design or content presentation method, so instructors are required to continuously monitor whether learners understand and focus on the knowledge given in the learning process (Kim, D. I., & Han, A. N., 2003). In addition, instructors should establish a framework for organizing and managing online learning content to ensure the quality of higher education in online learning and improve learners' academic commitment to online learning. In addition, it is expected that discussions and the search for concrete solutions are needed so that they can be practically applied in the online education scene.

Meanwhile, advances in neuroscience technology have expanded knowledge of the brain and learning (Sousa, 2009). Brain waves, also known as electroencephalography (EEG), record the dynamic electrical activity of neurons, which are cerebral neurons, and can analyze quantitative signals to extract information related to brain function. In particular, it can be seen that as EEG is activated, learning to process and store information is more likely to occur in the sensory organs (Jeong, C. G. et al., 2014). EEG is classified into delta, theta, alpha, beta, and gamma waves according to their frequencies. In learning, the EEG activity of theta, alpha, beta, and gamma waves demonstrate that the learning process is occurring in the cerebrum. Delta waves are excluded from the analysis because they are activated during deep sleep of normal people and do not apply to the study at hand. (Lee, S. A., 2021; Cho, H. W., 2019; Hwang, T. K., 2012). Theta waves are related to the basis of learning and memory, and the activation of alpha waves reflects the steady state of the brain. Beta waves are activated as concentration levels increase, and gamma waves are confirmed to be activated when high-dimensional cognition occurs (Eun, H. J., 2019; Jeon, H. J., & Lee, S. H., 2016; Choi, K. K., 1999; Jensen, Kaiser, & Lachaux, 2007; Wang, 2010).

This study aims to objectively analyze learners' cerebral cognitive activities using bio-signals from a brain science perspective by exploring the difference in EEG activity of technical college students according to online learning content type. To this end, the learner's EEG activity was measured while viewing one of the four types (instructor-centered type, instructor-text-centered type, text-centered type, and video-centered type). As a result, the activity of theta, alpha, beta, and gamma waves in the frontal lobe was confirmed through measured EEG. Furthermore, the learner's cerebral cognitive activity during online learning was established by EEG frequency analysis and EEG AC (attention and concentration) analysis. The significance of this study is that the learning effect of the frontal lobe according to the type of online learning content is measured by EEG activity which is objective data. Thus, the results are expected to provide essential data for online class design.

Research Design & Methods

Research Plan. This study analyzed learners' EEG according to the type of online learning content designed for K College University students after obtaining approval (40525-202108_HR-055) from the Institutional Review Board (IRB). The online learning content type is an independent variable and a treatment variable. There are four online learning content types namely, instructor-centered type (Face+Voice), instructor-text-centered type (Face+Voice+Text), text-centered type (Text+Voice), and video-centered type (Video). EEG activity of the learner was measured while watching one of the online learning contents by type. Through the measured EEG, the activity of theta, alpha, beta, and gamma waves in the frontal lobe of the cerebrum was confirmed, and the learner's cerebral cognitive activity during online learning was confirmed by EEG frequency analysis and EEG AC analysis. All experiments were conducted directly by the researcher to control researcher variables that may affect the research results.

Subjects. 24 students from K College University were selected for the study, and the criteria for selection were as follows. First, those who understood the purpose of this study and agreed to participate were selected. Second, in order to control the characteristics that are likely to affect EEG activity due to asymmetry between the left and right brains, the selected subjects were limited to right-handed students. Third, in order to control the characteristics that can affect EEG measurement, those free from cardiovascular disease, such as high blood pressure or arrhythmia, those without a history of neurological disease or disorders, and those without mental illnesses reported within the last six months were targeted. Fourth, to control variables in various situations due to age, the subjects selected were between

20 and 23 years old. A cohort was formed taking into consideration the year and academic scores of the subjects and divided into four groups.

EEG Tool. Muse 2 is a portable EEG measuring device developed in 2018 by InteraXon, Canada, that is harmless to the human body. All safety information was checked in advance. EEG measurement can be easily measured through simple contact without physical intervention using non-invasive dry technology, and it is suitable for use as an EEG measurement device for educational research due to its low EEG measurement time. Statistically similar results can be obtained using expensive EEG measuring equipment that measures EEG using low-cost portable, easy-to-use EEG measuring instruments or conductive gels and the attachment of electrodes (Krigolson, Williams, Norton, Hasall, & Colino, 2017). In particular, software provided by developers can convert the raw EEG analysis data for effective use in research (Duvinage, Casters, Petieau, Hoellinger, Cheron, & Dutoit, 2013; Kuziek, Shienh, & Mathewson, 2017). The extracted EEG analysis data can be programmed in mathematical language and stored as a text file, and various statistical analyses are possible (Jung, K. Y., 2002).

Online Learning Content. The online learning content featured in this study was created by the regional distance education support center designated by the Ministry of Education and KERIES. A collaborative effort of content creators in the region, the content was created for free use by regional educational institutions. The content used in this study was developed and produced by the researcher, and it has been used in online liberal arts classes in regional technical colleges since the second semester of 2021. The online learning content was revised and supplemented through expert validity verification through analysis of the needs of technical colleges and literature review. To produce the final version of the online learning content, four educational engineering experts and six video production experts were consulted to verify the validity of the content. Online learning content is divided into four types. First, the instructor-centered type (Face+Voice) is an online class that shows the face of the instructor and proceeds only with the instructor's explanation without reference materials. Second, the instructor-text-centered type (Face+Voice+Text) simultaneously displays the instructor's face and prepared text data on the screen along with the instructor's explanation. Third, the text-centered type (Text+Voice) focuses on the text presented on the video screen while listening to the instructor's voice. Finally, the video-centered type (Video) is an online learning type that consists of movies, subtitles, music, text, etc., combined without an instructor. All four content types are composed of the same content and length, and the video playback time is 4 minutes and 30 seconds, respectively.

Main study. Taking into consideration the year and academic scores of the 24 students of the study subjects, cohort groups were formed by dividing them into four groups of six. In this experiment, EEG measurements were performed on one student in one laboratory according to the scheduled order. All studies were conducted wearing masks to comply with the COVID-19 prevention rules. For the subject to be able to measure EEG in a relaxed state, the subject was asked about their state, mood, and well-being upon arrival at the laboratory. In addition, the subject was guided so that they could engage in the study with a sense of stability. The wearing of the EEG device was based on the 10-20 International Electrode Placement Method, and the positions of two electrodes, the left frontal lobe (AF7) and the right frontal lobe (AF8), were worn as active sites. A mobile phone app connected to an EEG device confirmed whether the EEG device was mounted correctly according to the 10-20 International Electrode Placement Act. Learning is a series of processes of recognizing and accepting information with eyes open. Therefore, in accordance with the purpose of this study, EEG data activated while watching online learning contents by type with eyes open rather than with eyes closed was used as research analysis data.

Data Analysis. The data collected in this study was analyzed using Mind Monitor, SPSS 21.0, and Excel according to the research problem in the following way. First, EEG frequency analysis uses quantitative characteristics for each frequency of EEG to measure EEG vibrations caused by the interaction of cerebral nerve cells with Mind Monitor and displays them as numerical values. According to the four types of online learning content, gamma analysis of the frontal lobe was performed using alpha wavelet statistics (e.g., Face+Voice+Text), text-centered type (Text+Voice), and video-centered type (Video). Second, EEG AC Activity was calculated as the ratio of theta, alpha, and beta waves related to attention and concentration among EEG frequencies. Third, the activated EEG frequency was modified using power spectrum analysis using SPSS 21.0 to analyze EEG AC for cognitive action in the cerebrum during learning.

Results

1. EEG Frequency Analysis Results According to Online Learning Content Types

To fulfill the purpose of this study, EEG frequency analysis was conducted to determine whether there is a difference in theta, alpha, beta, and gamma activity of the frontal lobe integration (AF7+AF8), which is the sum of the left frontal lobe (AF7) and right frontal lobe (AF8), depending on which of the four online learning content types was used. EEG is classified into theta waves (4 to 8 Hz), alpha waves (8 to 13 Hz), beta waves (13 to 30 Hz), and gamma waves (30 to

50 Hz) according to its frequency, and each frequency has unique characteristics. Theta waves are brain waves associated with the basis of learning and memory (Eun, H. J., 2019), while alpha waves are activated when the brain is in a relaxed, stable state. They are closely related to memory and information processing speed (Park, K. S., 2007; Bayeens, Vansteinwegen, Hermans, & Ellen, 2001). Beta waves are activated when high concentration is exerted (Kim, E. M., 2013; Park. K. S., 2007). Gamma waves are activated during high-dimensional cognitive activities by integrating multiple senses (Jensen, Kaiser, & Lachaux, 2007; Wang, 2010). Table 1 shows the results of EEG frequency analysis according to the online learning content type. Theta wave and alpha wave activity were highest with the video-centered type (Video) at 1.250 points and 1.335 points, respectively, and beta wave and gamma wave activity were highest with the instructor-text-centered type (Face+Voice+Text) at .886 points and .485 points, respectively.

Table 1

EEG Frequency Analysis Results According to Online Learning Content Types

Category		Theta wave		Alpha wave		Beta wave		Gamma wave	
	n	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Instructor-centered type (Face+Voice)	6	.981	.611	1.074	.401	.739	.449	.339	.596
Instructor-text-centered type (Face+Voice+Text)	6	.952	.659	1.148	.442	.886	.363	.485	.773
Text-centered type (Text+Voice)	6	1.148	.698	1.146	.508	.780	.711	.398	.837
Video-centered type (Video)	6	1.250	.625	1.335	.461	.812	.456	.285	.616
Total	24	1.084	.661	1.176	.465	.804	.515	.376	.716

2. EEG AC Analysis Results According to Online Learning Content Types

Among the measured EEG Activity analysis values, the EEG AC was calculated through power spectrum analysis using the ratio of alpha waves and beta waves, which are related to attention and concentration, and theta waves which are associated with the stable state. In order to obtain the EEG AC, the sum of the total number of alpha waves and the total number of beta waves is divided by the total number of theta waves. Power spectrum analysis aims to identify the proportion of each frequency by classifying the values of the frequency domain (Park Jin-hyuk, et al., 2018), and the calculation results are shown in Table 2. The EEG AC average is 1.889. The instructor-text-centered type (Face+Voice+Text) had the highest EEG concentration with 2.187 points, followed by the instructor-centered type (Face+Voice) with 1.919 points, the video-centered type (Video) with 1.736 points, and the text-centered type (Text+Voice) with 1.715 points.

Table 2

EEG AC Analysis Results According to Online Learning Content Types

Category		EEG AC	
	n	*M*	*SD*
Instructor-centered type (Face+Voice)	6	1.919	.631
Instructor-text-centered type (Face+Voice+Text)	6	2.187	.578
Text-centered type (Text+Voice)	6	1.715	.724

Category		EEG AC	
Video-centered type (Video)	6	1.736	.348
Total	24	1.889	.580

Discussion

Based on the research results, the following discussion focuses on the areas where the difference in EEG activity has been identified according to the type of online learning content.
First, according to EEG frequency analysis, the instructor-centered type (Face+Voice) showed overall lower EEG activity compared to other online learning content types. The learner's alpha and beta waves showed the lowest activity. Alpha waves are closely related to the speed of information processing in a relaxed state. Beta waves are activated when attention is exercised in high-level cognitive activities (Eunheon-jeong, 2019; Kyung-gyu Choi, 1999). It was found that the theta waves, produced in stable situations, and the gamma waves, produced in high-level cognitive activities, were also activated at below-average levels. On the other hand, the instructor-centered type (Face+Voice) showed an above-average concentration as a result of EEG AC analysis. According to previous studies, beta waves are activated when learning information is input from the outside, and theta and alpha waves are activated when the learner internally processes learning information input from the outside (Kim Yong-jin, 2000). In other words, in the instructor-centered type (Face+Voice), the learner can concentrate and process information inputted from the outside for a short time through online learning. However, it seems like there is difficulty internally processing the input information.

Second, as a result of EEG frequency analysis, it was found that with the instructor-text-centered type (Face+Voice+Text), beta and gamma wave activity dominated, whereas theta wave activity was lowest. Beta waves, activated in learning situations, are brain waves that are mainly generated when solving problems requiring concentration or listening to or speaking verbal explanations. Previous studies have shown that beta waves are activated when making decisions through logical reasoning (Kang Young-hee, 2015; Park Sang-nam, Kim Young-hwal, 2008; Choi Yoon-sik, 2014; Hwang Tae-kyung, 2012). According to brainwave research, gamma waves activated in learning situations are activated in high-level cognitive processes that result in comprehension through mental effort (Jung-Beeman et al., 2004), and gamma waves activated in the frontal lobe are interpreted as the expression of cognitive learning processes through perception and information processing (Lee Sun-ah, 2021). Out of the four types, this type appeared to generate the highest levels of EEG AC. In other words, the instructor-text-centered type (Face+Voice+Text) is the most effective online learning content type to generate learners' concentration and high-dimensional cognitive activities in online learning.

Third, EEG frequency analysis of text-centered type (Text+Voice) showed higher-than-average theta and gamma wave activity of the frontal lobe of the cerebrum during online learning with this type. Considering the high activation of theta waves, it can be interpreted that the learner is a little tense. Still, the activity of the gamma waves show that the brain is working to process information through a high degree of cognition. According to another study, theta and gamma waves rise simultaneously when learners learn visually and aurally using short-term memory. This can be interpreted as the result of activation of the Broca's and Wernick's areas, which are the core language centers of the frontal lobe (Yeon-hee Kim et al., 2000). Furthermore, the theta waves, activated to abnormally high levels during learning, show the state where both eyes are open, but the brain appears to be asleep, so learning cannot occur. According to previous studies, hyperactivation of theta waves is found in most learners with poor memory or distracted attention (Park Byung-woon, 2005). According to the EEG AC analysis results, the EEG AC of the text-centered type (Text+Voice) was the lowest.

Fourth, the video-centered type (Video) is a class conducted using scenes from a movie or videos containing class-related content. As a result of EEG frequency analysis, while learning this content, the learner showed the highest level of theta and alpha wave activation in the cerebral prefrontal brain. However, the activity of gamma waves in the video-centered type (Video) was the lowest of the four online learning content types. Therefore, according to the EEG AC analysis results, it is confirmed that learners exhibited below-average EEG attention concentration in the video-centered type (Video). According to previous studies, the high activation of prefrontal theta waves and the increased activation of prefrontal beta waves can be interpreted as a cerebral cognitive process for the memory of short-term memory tasks (Ko Byung-jin, 2010; Jung Ae-jin, 2016). In other words, in classes conducted with the video-centered type (Video), information is processed while learners are relaxed, and short-term concentration is exhibited. However, it is expected that generating a high level of cognitive action or attention in this online learning content will be challenging. For this reason, it can be inferred that learners using video-centered type (Video) classes may forget the learned content as time elapses.

Conclusion

First, in the instructor-centered type (Face+Voice), low levels of alpha and beta waves were activated in online learning, but EEG AC showed above average. As a result of EEG analysis, it can be predicted that this online learning content type is sufficient to arouse learners' curiosity due to brain stimulation. Still, it will be challenging to process externally input information internally or maintain concentration. For this type, it was confirmed that learning information was input, but the input information was not processed internally. First, in the instructor-centered type (Face+Voice), low levels of alpha and beta waves were activated in online learning, but EEG AC showed above average. As a result of EEG analysis, it can be predicted that this online learning content type is sufficient to arouse learners' curiosity due to brain stimulation. Still, it will be challenging to process externally input information internally or maintain concentration. For this type, it was confirmed that learning information was input, but the input information was not processed internally.

Second, the instructor-text-centered type (Face+Voice+Text) showed the highest beta and gamma wave levels among the four types and the highest EEG AC. This characteristic appears when performing cognitive tasks according to working memory during learning, and this type can be said to be the most suitable type for online learning. In addition, learners perceived this type to be the most similar to face-to-face classes.

Third, in the text-centered type (Text+Voice), the activity of the theta and alpha waves overlapped, and it was found that the theta and gamma waves were highly activated. The hyperactivity of theta waves is a phenomenon found in a state of distraction or memory loss. Therefore, the possibility of a decline in cognitive processing due to a lack of information provided by the online learning content type can also be predicted. Alternatively, this online learning content type showed a state of concentration on linguistic characteristics due to the processing of text information by the cerebrum.

Fourth, the video-centered type (Video) showed the highest activity of theta and alpha waves among the four types and the lowest activity of gamma waves. In other words, with video-centered type content, the student can process the information in a relaxed state, and concentration levels are high. However, although information processing does occur, it is difficult to achieve high levels of cognitive action.

In summary, rather than adhering to the characteristics of one type of online learning content and conducting the class accordingly, the effects of learning can be maximized if the online learning content is configured and conducted according to the suitability for the class design. In other words, at the beginning of online learning, the instructor-centered type (Face+Voice) that induces the learner's short-term concentration should be used, but the overall operation of the class should be conducted using the instructor-text-centered type (Face+Voice+Text). Important concepts and theory-oriented classes should employ the text-centered type (Text+Voice), after the learner's concentration rapidly decreases, the video-centered type (Video) should be used. Through effective class design, cerebral cognitive action in online learning will be possible.

This study is meaningful because it provides more objective results on the learning process for online learning content types by focusing on the learner's cognitive activity from a brain science perspective of online learning by incorporating neuroscientific EEG activity into the pedagogical aspect. Classes using online learning content are classes in which the instructor records the class content in advance and delivers the content as a video. Thus, direct intervention by the instructor is not possible during the class, and cognitive overload can occur in the learner depending on the online learning presentation method. In this respect, this study is meaningful in that it explores the learner's cognitive process in online learning through neuroscience and applies the results of exploratory research on the brain and learning to educational situations. In particular, the difference in EEG activity of learners in online learning was confirmed through EEG, an objective indicator of brain activity occurring in the process of transferring information in the brain. This study is expected to provide essential data to prepare an effective online learning design plan.

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