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Brain Wave Application in E-commerce Discipline

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In this study, we examined the live streaming training process for e-commerce hosts, focusing on how changes in students' attention and cognitive states affect the effectiveness of live streaming practice. In the experiment, a headband device from Benegear Inc. was utilized to collect and analyze electroencephalography (EEG) data in real time. The physiological signals, collected by the headband sensor, comprised five foundational brainwave values and their derived cumulative metrics, which were primarily used to indicate differences in attention levels across various states. Nine students were selected to participate in the training experiment. The results revealed that although the students' attention tended to decline during trial broadcasts, their cognitive processing capabilities improved, as indicated by brainwave activity. This suggests that various factors, including environmental ones, impact the attention of live stream hosts during broadcasts. The study highlights the potential of EEG technology in e-commerce education, and we propose innovative teaching approaches aimed at managing emotion and attention. These approaches seek to optimize training programs, enhance the skills of live stream hosts, and adapt to the rapid developments in the e-commerce industry.

1. Introduction

The electronic commerce industry, commonly known as "e-commerce," has gradually become an essential part of the global economic system. Its market size continues to grow, and competition is becoming increasingly intense. The rapid rise of the e-commerce sector has not only transformed consumer purchasing behaviors but has also placed higher demands on practitioners in terms of professional skills, psychological resilience, and operational efficiency.

In today's fast-paced and high-pressure work environment, e-commerce professionals—particularly live stream hosts—must rapidly and effectively process complex information. They are required to engage in timely, real-time interactions with customers while maintaining a keen awareness of market dynamics. In this context, the ability to regulate emotions and manage attention has become essential for enhancing work efficiency, customer satisfaction, and the

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overall competitiveness of businesses. The effective management of these skills is directly linked to fluctuations in sales performance. By incorporating various deliberate practice strategies into professional education, we can strengthen students' emotional regulation and attention management capabilities.

Zhang described attention as the state of mental activity or consciousness focused on a specific object at a given moment.(1) For e-commerce practitioners, managing attention requires both high concentration and the ability to quickly shift focus. Moreover, effective attention management can greatly enhance work efficiency and the accuracy of decision-making in key areas such as information processing, customer service, and market analysis.

In a world overflowing with data and rapidly evolving market conditions, e-commerce professionals must continuously learn and adapt to changes. They also need to maintain emotional stability in an uncertain environment to ensure their attention remains sharp and flexible.

Given these challenges, educators teaching e-commerce in colleges and universities need to understand the attention characteristics of e-commerce practitioners. It is essential to select appropriate teaching strategies that effectively cultivate students' comprehensive skills, enabling them to thrive in changing environments.

2. Study of Brain Waves

2.1 Research relative to attention, emotions, and cognitive decision-making

Brain waves are a direct indicator of brain activity and have attracted considerable attention in recent years, particularly in research related to attention, emotions, and cognitive decision-making. Zhu *et al.* explained the fundamental principles of brain waves and identified at least four frequency bands: δ (delta), θ (theta), α (alpha), and β (beta). These frequency bands are closely associated with the brain's active state. Their work has established a theoretical foundation for further studies in this area.(2)

In attention research, electroencephalography (EEG) signals provide valuable insights into brain activity, allowing researchers to study various factors such as attention levels, IQ scores, and relationships between working memory load and cognitive control processes. Additionally, innovative EEG signal applications enhance studies focusing on auditory attention detection. For instance, Zhang *et al.* developed an attention training system that leverages brainwave characteristics. This system effectively improved students' attention levels by offering targeted training suggestions and incorporating a new teaching tool.(3) Chen *et al.* discovered a linear relationship between the IQ score and the intensities of the α and β frequency bands in brainwaves. This finding offers valuable insights into the factors that influence IQ and presents a new opportunity for potential IQ improvement.(4) Research conducted by Wei and Zhou demonstrated the link between working memory load and cognitive control processes using EEG signals.(5) In several studies, the connection between EEG and auditory attention has been explored. The research conducted by Hölle *et al.* demonstrated the feasibility of investigating auditory perception in real-world settings using long-term ear-EEG.(6) Cai *et al.* conducted research on a spiking graph convolutional network (SGCN) that effectively captures the spatial characteristics of multichannel EEG data in a biologically plausible way.[7] The SGCN demonstrates competitive performance in auditory attention detection, particularly in environments with low-latency and low-density EEG settings.[7]

Zhang's team identified subjects' emotional states using EEG signal recording, preprocessing, feature extraction, and classification algorithms, paving new paths for emotional analysis in human–computer interactions.[8] Gu *et al.* proposed an innovative frame-level teacher–student framework with data privacy for emotion recognition using EEG signals. This framework enables continuous optimization and enhancement by training the next student subnetwork only on new EEG data.[9] Wang *et al.* introduced a novel deep learning framework called the frame-level distilling neural network. This framework effectively identifies relationships among various frames and facilitates the automatic extraction of refined high-level features relevant to emotion recognition.[10]

In the context of cognitive decision-making, several studies have provided both quantitative and qualitative theoretical references for establishing evaluation standards of brain cognitive functions. This is achieved by analyzing brainwave activity during various cognitive decision-making tasks. Wang *et al.* extracted and analyzed the average spectral power and phase synchronization values of different brainwave frequency bands (δ, θ, α, and β) across multiple subjects. They employed time–frequency analysis methods for EEG signals, which have garnered significant attention owing to their capability to provide real-time information about brain activity.[11] Anderson *et al.* described the design of the user study, the process of extracting cognitive load metrics from EEG data, and the application of these metrics to quantitatively assess the effectiveness of visualizations.[12] Cozac *et al.* reported that a total of 24 studies have documented findings related to quantitative EEG (QEEG) across various cognitive states in individuals with Parkinson's disease (PD). Additionally, the QEEG variables showed a correlation with cognitive assessment tools over time.[13]

2.2 Research related to marketing and e-commerce

EEG signals can be used in fields such as online shopping addiction treatment, neuromarketing, and e-commerce reviews. In Yang's article, he explored the psychological dependency mechanisms of online shopping addiction and highlighted its significance as a psychological phenomenon.[14] Panda *et al.* tackled challenges in neuroscience-driven marketing research by proposing a neuro-marketing framework based on EEG signals, which incorporates deep transfer learning, spatial attention models, and deep neural networks.[15] Their research results offered new insights into building universal consumer preference models that apply across various subjects, sessions, and tasks. Additionally, Yazid *et al.* demonstrated that a statistically significant high brain activity observed while participants watched the video advertisement indicated its correlation with short-term memory, which was enhanced by visual stimuli.[16] Bai *et al.* discussed that social commerce reviews (SCRs) elicited higher P300 amplitudes than e-commerce reviews (ECRs) when SCRs and ECRs were used as stimuli to evoke event-related potentials. This finding indicates that subjects paid more attention to SCRs.

Their research provided a new perspective on the application of EEG in studying social commerce and e-commerce.[17] Bazzani *et al.* noted that the current literature provides limited insights into the use of multisensory or interactive stimuli.[18] Furthermore, it is essential to address ethical considerations related to participant privacy and research integrity in EEG-based research. This focus is vital for ensuring transparency and building trust among participants.[19]

Brain waves hold significant potential for studying attention, emotions, and cognitive decision-making. A detailed analysis of their characteristics can enhance our understanding of how the brain functions. This analysis offers a research framework for e-commerce education and provides both scientific and practical methods for the practical application of e-commerce education. The brain's activity is indicated by changes in EEG data. Our research is aimed toward enhancing our understanding of brain processes through brain wave measurements and to develop effective training courses. Additionally, utilizing these methods, effective training programs can assist hosts in achieving their optimal working state, which in turn enhances the effectiveness of live streaming. Different brain wave bands have unique characteristics and mechanisms of action. A thorough investigation into these bands, alongside an understanding of the brain's operational principles, will provide essential practical guidance for research in fields such as computer artificial intelligence, neuroscience, psychology, and cognitive science.[20]

It is common to utilize brain wave research in specialized groups and business activities related to consumer behavior. However, there has been less focus on applying this research to the behavior of electronic industry practitioners. We aim to conduct in-depth research to gain a better understanding of how brain waves influence mood and attention. Our goal is to alleviate the work-related stress of electrical industry practitioners and enhance their work efficiency.

3. Materials and Methods

3.1 Participants and background

The authors are located in China's most abundant fishery region, and the product sold in this study is golden pompano. E-commerce serves as a platform, whereas live-streaming selling leverages the functionalities of e-commerce platforms to interact with a broad potential customer base. Therefore, it requires not only product sales skills but also interactive techniques to complete promotions within a limited time. This study involved nine undergraduate students who were undergoing training to become e-commerce live stream hosts, who promote and sell products through real-time video broadcasts. Initially, over 100 individuals applied, of which 30 were shortlisted in the preliminary round. Following an initial assessment, nine participants were ultimately selected for the final training phase. These participants started a live-streaming skills training program two weeks prior to the experiment. The program was designed to include trial broadcasting practices, which would take place two weeks after a brief professional training session aimed at enhancing their skills through practical exercises. The participants had a solid understanding of live-streaming techniques and had taken part in several trial broadcasts. It is important to note that prior to the formal collection of EEG data, the instructors responsible for the live-streaming training repeatedly emphasized its significance, encouraging the students to approach it with seriousness. This likely enhanced their focus on practical activities. Additionally, all participants had engaged in at least one observational internship, which provided them with firsthand experience of the live-streaming process.

3.2 Experiment tasks and equipment operation

Before starting the experiment, the researchers provided each participant with a headband device from Benegear Inc. Figure 1 demonstrates the use of the head-mounted device. Figure 1(a) shows its original design with descriptions. Figure 1(b) shows the modified hat-mounted version designed for the live streamer. Figure 1(c) depicts a practice session simulating a live commerce broadcast, and Fig. 1(d) presents a real-time scenario of an ongoing live commerce

Fig. 1. (Color online) Device usage. (a) Original design. (b) Hat-mounted version for the live streamer. (c) Live commerce broadcast simulation. (d) Scenario of real-time live commerce broadcast selling session.

broadcast. The instructor made sure that the headband's EEG data collector made proper contact with the battery's metal plates and checked that the headband's indicator light showed a green signal, which indicated sufficient battery power. A red light would indicate insufficient battery power. To ensure proper placement of the headband, the researcher positioned the metal plates snugly against the participant's forehead. The participants were also required to keep their foreheads dry and free of sweat. After that, they should open the app on their smartphones, which was developed by Benegear Inc., and connect the headband device from the list of available devices by selecting the corresponding device number. After 20 seconds of correctly wearing the headband, the app displayed a "Connected" status. The headband's EEG data collector then began operating, initiating the real-time collection of the participant's EEG data. The EEG signals are received via a Bluetooth receiver. Both the software for processing the received data on the PC end and the receiver were purchased from Benegear Inc., which is responsible for software version updates and hardware maintenance. In addition to the PC-based receiving software, the company also provides a mobile app for reading the device's signals. Figure 2 shows the real-time data interface of the connected device in this app.

3.3 Data acquisition and collection

The hardware designed for this project captures brainwave signals, categorized into δ, θ, α, β, and γ waves. These signals are accumulated at 6 s intervals and updated in real time. Two key metrics are derived from the data: the thinking index (reflecting cognitive confusion) and the

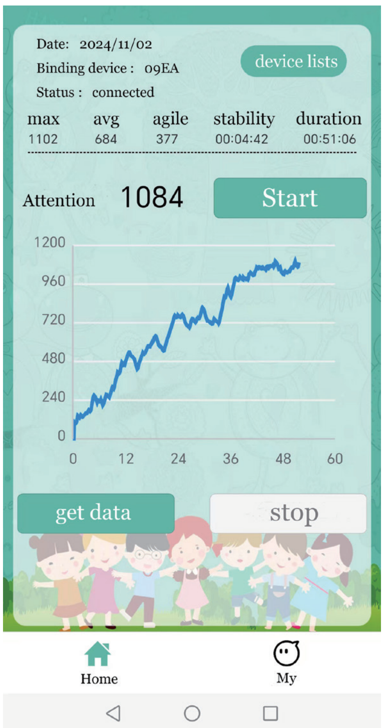

Fig. 2. (Color online) Mobile app interface from Benegear Inc. for monitoring.

concentration index (representing the focus level). The collection and analysis of these indices provide a critical foundation for further research on participants' attention, emotion management, and cognitive states during live streaming. As shown in Fig. 2, the real-time monitoring interface on the smartphone displays the user's concentration index and its fluctuations.

We employed a mixed-methods approach, incorporating observation, data collection, and interviews to conduct a comprehensive analysis of the trial process. Specifically, once the subject properly wore the headband, the researcher began collecting brainwave data. At the same time, using both a mobile app and a computer monitoring interface, real-time observation of the training environment was enabled as participants engaged in e-commerce live stream training.

The monitoring covered multiple aspects, including interactions between students and teaching assistants, emotional expressions of students and instructors, as well as the performance and collaboration of the live stream support team—composed of operational staff and the integrated streaming team. Throughout the process, all EEG data were converted into numerical values, including the thinking index and concentration index, and were downloaded at the end of the session for comparison with overall emotional states.

3.4 Training process for e-commerce live streaming

The entire process of e-commerce live streaming training is as follows.

(1) Entering the live streaming simulation environment: Students begin by entering a pre-arranged live streaming setup to prepare for the upcoming training activities.
(2) Wearing the headband device: Students correctly put on the headband device, which activates the data collection system necessary for analyzing brainwave data.
(3) Trial explanation: The instructor explains the purpose of the test in detail, instructing students to conduct their e-commerce live streaming activities normally and naturally while wearing the headband. This stage lasts approximately 10 minutes.
(4) Pre-live streaming briefing: Before starting the live stream, the teacher provides information about the relevant content, including the live streaming process and important precautions to take. This briefing lasts around 15 minutes.
(5) Script and content reinforcement training: Students participate in reinforcement training for the script and content they will use during the live stream. This phase also lasts approximately 15 minutes to enhance the effectiveness of their broadcast.
(6) Trial live streaming: Students enter the trial live streaming phase, which is a real online live stream accessible only to invited fans. This phase lasts 30 minutes, allowing students to familiarize themselves with the live streaming process through practical experience.
(7) Real online live streaming: Finally, students conduct an official online live stream, engaging with a global audience. They apply the skills they have learned in a real-world scenario.

4. Experimental Results

In this study, nine undergraduate students participated in live-streaming training for e-commerce anchors. Table 1 presents the basic information of the participants and the serial

Table 1
Basic information of the participants.

Device Number	Gender	Age	Training duration	Year of study	Major
A30E	Female	20	over 12 hours	Sophomore	E-commerce
A293	Female	20	over 12 hours	Sophomore	E-commerce
A29E	Female	20	over 12 hours	Sophomore	E-commerce
A2B6	Female	23	under 6 hours	Senior	Geographical Sciences
A300	Female	19	over 12 hours	Freshman	Communication
A2F9	Female	20	over 12 hours	Sophomore	E-commerce
A2A7	Female	20	over 12 hours	Sophomore	E-commerce
A2A5	Female	20	over 12 hours	Sophomore	E-commerce
9EDB	Female	20	over 12 hours	Sophomore	E-commerce

numbers of the head-mounted devices they used. The serial numbers were used to identify different subjects (e.g., the subject using the device with the serial number A30E was identified as subject A30E).

The serial number of the head-mounted device does not affect data collection. The collected data is saved in an XLS file format, with the header structure detailed in Table 2.

The table displays the relevant EEG data, including the calculated values for the thinking and concentration indices, which are collected every 6 s. The calculation of these two metrics is implemented within the IC chip, utilizing patented algorithms owned by Benegear Inc. However, the original data contained a substantial amount of noise, mainly owing to the weak nature of EEG signals, which are easily contaminated. Thus, the data cleaning process was conducted, focusing on removing noise data points.

After completing the data cleaning process, each participant was treated as a separate subject in the study. The relationships among the concentration index, thinking index, and the values of the α, β, and γ brain waves were analyzed. Figures 3–10 display the performance graphs for the eight subjects.

All figures adopt a dual-axis format. The three differently colored lines, as indicated in the legend, correspond to the left axis, whereas the black line corresponds to the right axis. The units for the left and right axes differ. The data from one subject was deemed invalid because of a power interruption during the data collection.

5. Discussion

During the training process of the test students, there were significant changes in their concentration and cognitive states at various stages. Specifically, when students first entered the room for live streaming, their concentration metrics were typically scattered around initial values. However, during the trial explanation and pre-live briefing sessions, the concentration metrics of two students consistently increased, surpassing the threshold of 2000–4000 $\mu V^2/Hz$.

Additionally, some concentration indicator values ranged from 200 to 800 $\mu V^2/Hz$, which represents the lower end of the noise power spectral density—essentially, the square of the noise voltage per unit frequency bandwidth (in Hz). For the remaining students, the indicator values generally fluctuated around 1000 $\mu V^2/Hz$. This finding highlights significant individual differences in concentration levels among students during the initial stages of receiving information and transitioning into a working state.

Table 2
Structure of data collected.

Start time	########										
Interval:	6269 ms		1320								
Time	δ	θ	α low	α mid	α high	β low	β mid	β high	γ	Thinking	Concentration
14:16:27	60000	1221	154	448	240	278	165	219	1134	999	30
14:16:33	22280	648	69	154	99	122	93	141	424	999	30

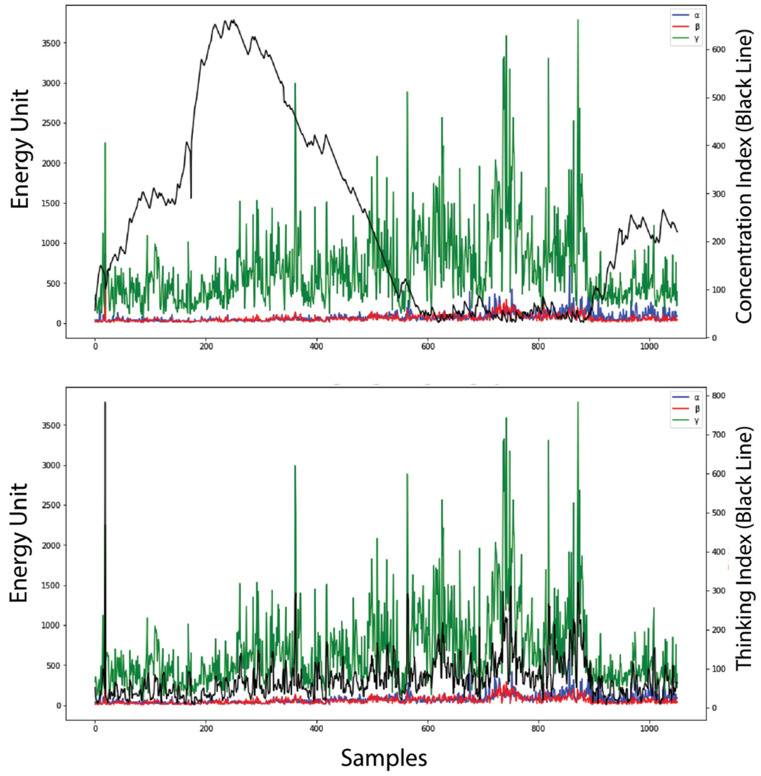

Fig. 3. (Color online) EEG patterns of thinking and concentration for subject A300.

After beginning training in live-streaming speech and memory enhancement techniques, all students demonstrated an upward trend in concentration levels. However, students who initially had higher concentration levels showed a more pronounced increase in these levels. This result further emphasizes the crucial role that concentration plays in knowledge absorption and skill reinforcement.

During the Trial Live Streaming stage, the research team observed an interesting phenomenon: the students' thinking indicators increased, whereas their concentration indicators significantly decreased. In-depth interviews with the students revealed that, contrary to expectations and reminders from the instructor, they did not fully focus on the live-streaming sessions. Instead, they began to divert their attention to external factors, such as the public screen of the live stream, guidance from the assistant instructor, operational tasks, comprehensive control, and their surroundings. This finding highlights the complexity of the live-stream training environment and demonstrates students' flexibility in making cognitive decisions in

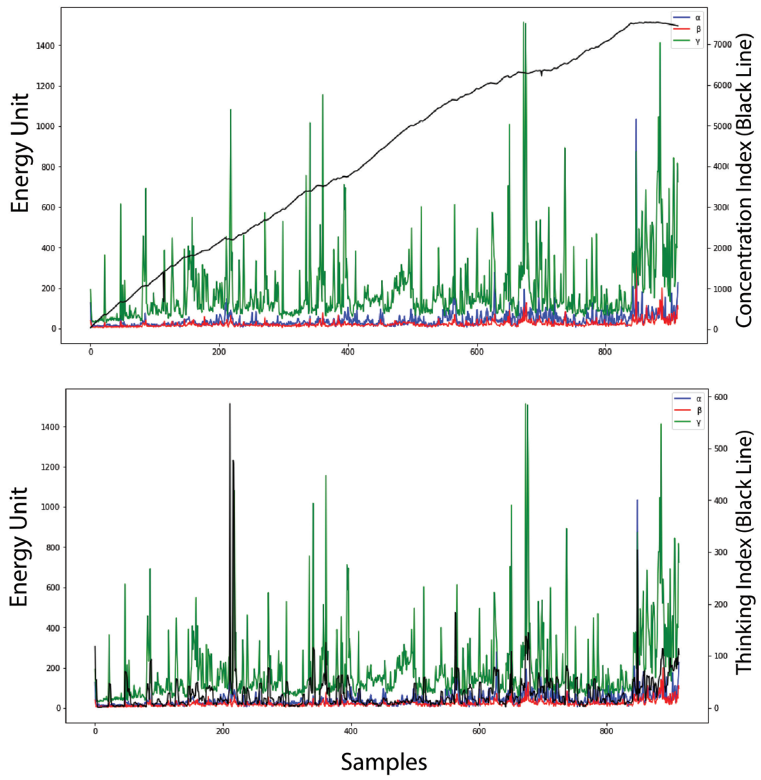

Fig. 4. (Color online) EEG patterns of thinking and concentration for subject A28C.

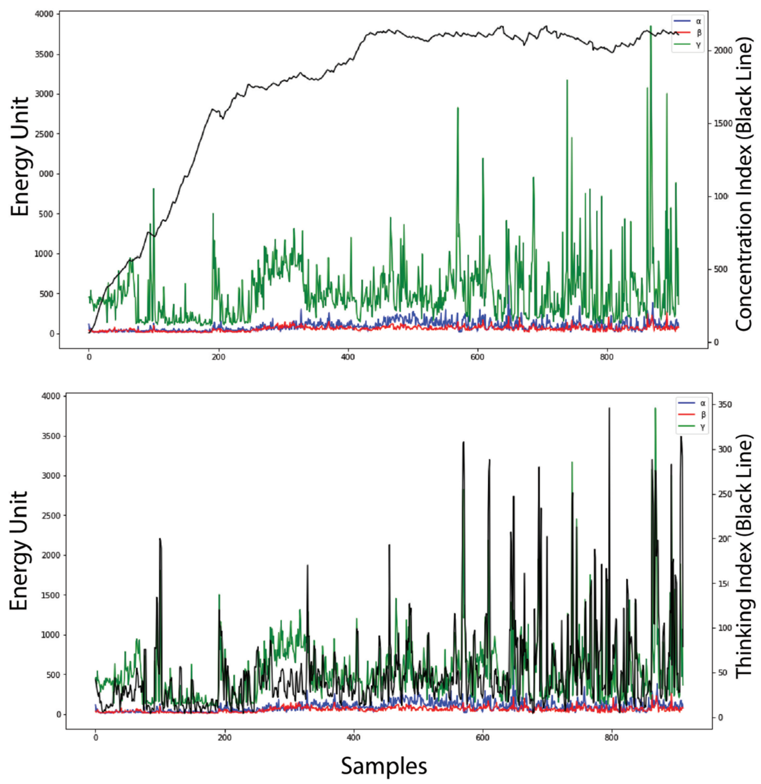

Fig. 5. (Color online) EEG patterns of thinking and concentration for subject A2F9.

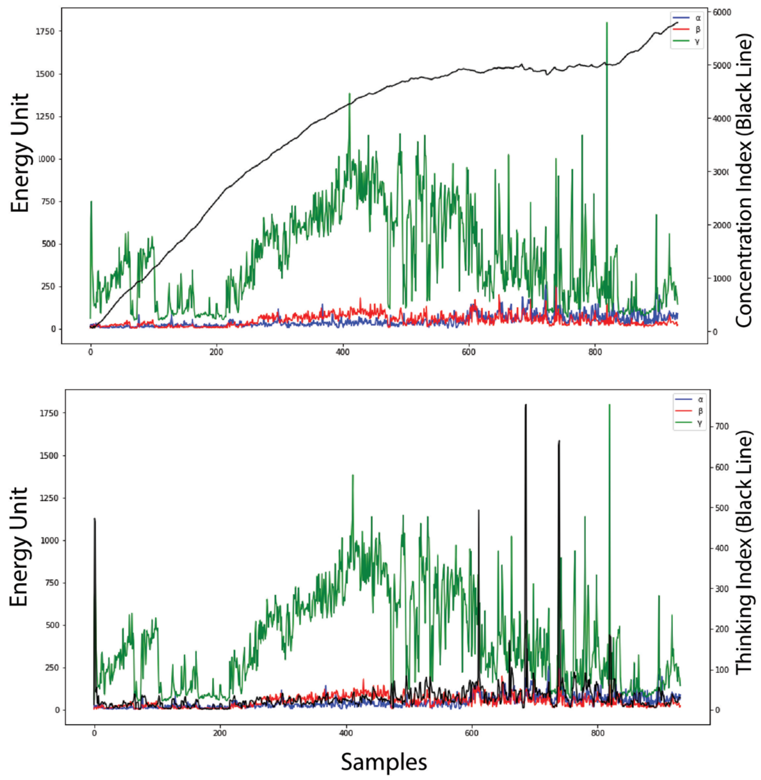

Fig. 6. (Color online) EEG patterns of thinking and concentration for subject A2A7.

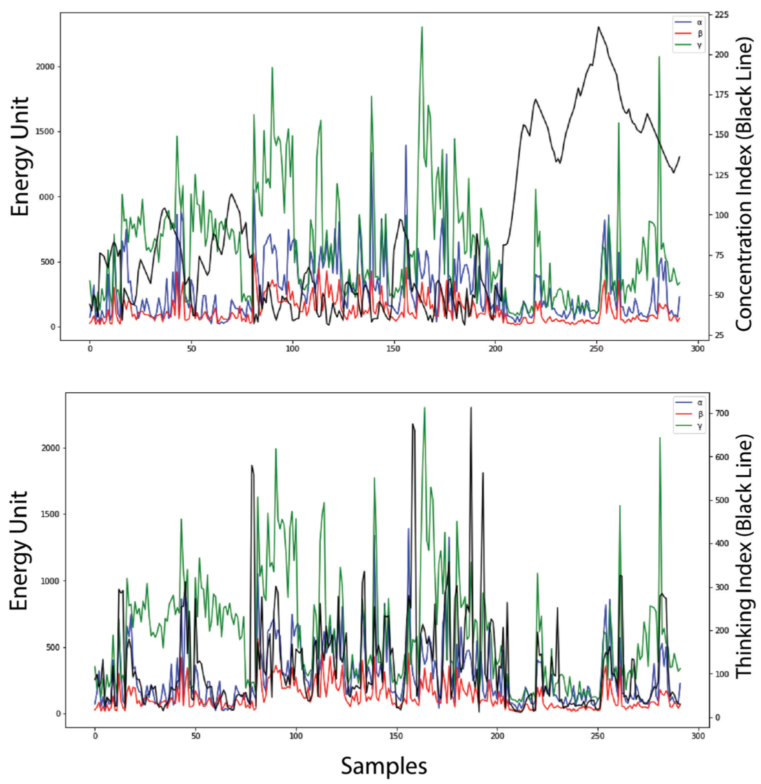

Fig. 7. (Color online) EEG patterns of thinking and concentration for subject A2A5.

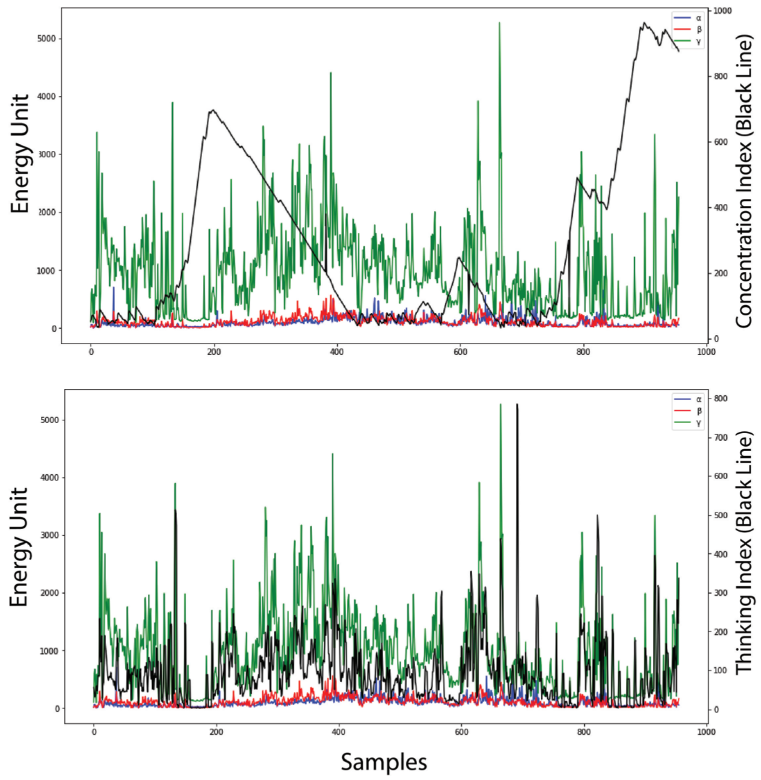

Fig. 8. (Color online) EEG patterns of thinking and concentration for subject A30E.

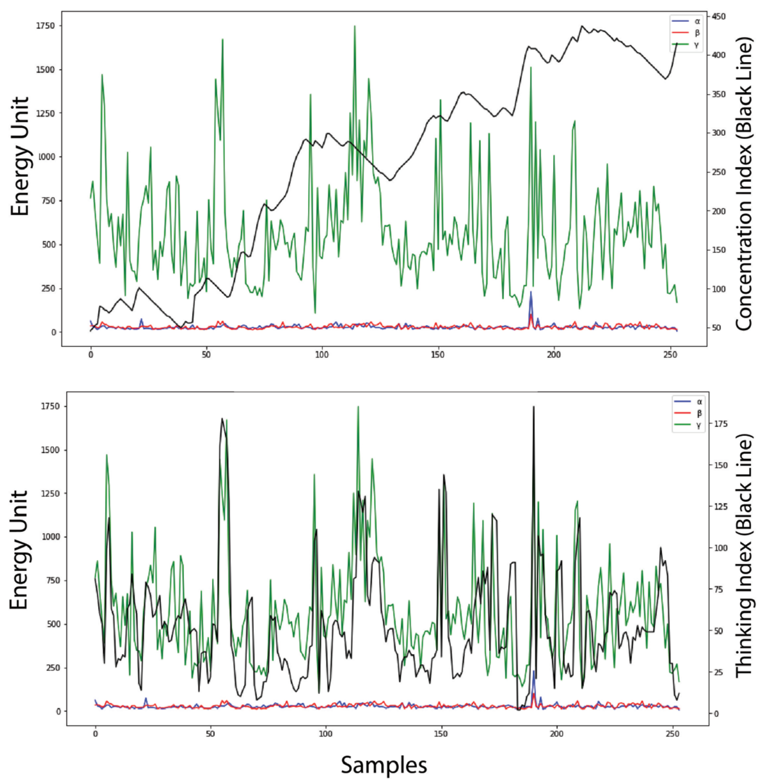

Fig. 9. (Color online) EEG patterns of thinking and concentration for subject 9EDB.

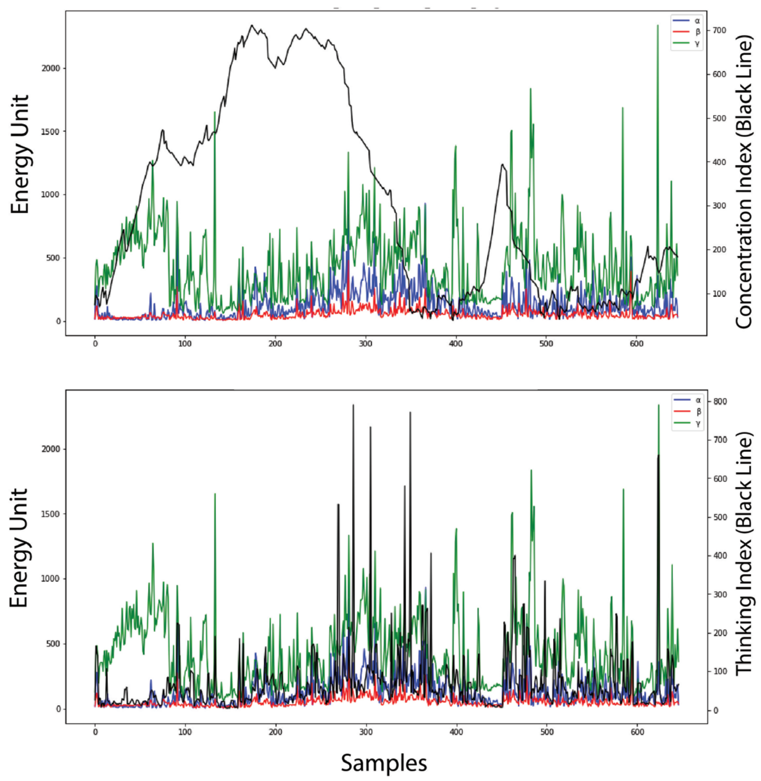

Fig. 10. (Color online) EEG patterns of thinking and concentration for subject A2EA.

real-time situations. Furthermore, students with higher thinking indicator values were more adept at handling and adapting to these real-time circumstances, underscoring the importance of the cognitive state during live-streaming training.

In this study, we investigated the evolving concentration and cognitive states of students during e-commerce live stream training. We further identified the underlying mechanisms through which these cognitive shifts affect training outcomes. The findings suggest that traditional training approaches are insufficient to meet the demands of contemporary e-commerce practitioners. Therefore, it is imperative to re-examine and innovate both training content and methodology to keep pace with the industry's rapid evolution.

In particular, in this research study, we sought to identify observable trends and patterns in host performance during e-commerce streaming. These well-defined patterns will, in the subsequent phase, form a basis for developing more effective training frameworks for live stream hosts. The research team remains committed to further exploring this field to provide scientifically grounded and practical guidance for the cultivation of effective e-commerce live stream hosts.

6. Conclusions

On the basis of the experimental findings of this study, we propose a practical framework for applying EEG technology to e-commerce live stream training, comprising three key implementation strategies.

(1) Personalized Training Protocol Design

EEG-based profiling enables the development of individualized training programs tailored to hosts' neurophysiological characteristics. By analyzing trainees' brainwave patterns during simulated live streams, we identify unique cognitive–emotional signatures that inform the customization of sales scripts and interaction frameworks. This data-driven approach optimizes skill development through personalized content delivery matched to hosts' innate neurological responses.

(2) Dynamic Teaching Methodology Implementation

The integration of real-time EEG monitoring creates an adaptive training environment that responds to trainees' cognitive states. Our implemented system detects attention lapses, cognitive overload, and emotional fluctuations during practice sessions, allowing instructors to make evidence-based interventions. This includes adjusting verbal pacing, modifying presentation complexity, and implementing just-in-time relaxation techniques to maintain optimal cognitive engagement throughout training simulations.

(3) Evidence-based Assessment System Integration

We have established a multimodal evaluation framework that combines quantitative EEG metrics with performance outcomes. This system correlates neural indicators (attention allocation efficiency, emotional regulation patterns) with key performance markers across different live-stream stages, from product presentation to customer interactions. The resulting analytics provide objective benchmarks for training effectiveness and create continuous feedback loops for program improvement.

These implemented strategies demonstrate how neurotechnology can transform e-commerce host training by bridging physiological monitoring with pedagogical methods. The framework offers a scalable solution for developing hosts' cognitive resilience and adaptive skills, ultimately enhancing training outcomes in fast-paced digital commerce environments.

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