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ORIGINAL RESEARCH

Multimodal Learning Analytics and Neurofeedback for Optimizing Online Learners' Self-Regulation

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Abstract

This report describes the use of electroencephalography (EEG) to collect online learners' physiological information. Recent technological advancements allow the unobtrusive collection of live neurosignals while learners are engaged in online activities. In the context of multimodal learning analytics, we discuss the potential use of this new technology for collecting accurate information on learners' concentration levels. When combined with other learner data, neural data can be used to analyze and predict self-regulated behaviors during online learning. We further suggest the use of machine learning algorithms to provide optimal live neurofeedback to train online learners' brains to improve their self-regulated learning behaviors. The challenges of EEG and neurofeedback in online educational settings are also discussed.

Keywords Multimodal learning analytics · Electroencephalogram · Neurofeedback · Online learners · Self-regulated learning

1 Introduction

Online learning with social isolation and a lack of immediate feedback presents unique challenges for learners in managing and maintaining learning, often leading to higher dropout rates than face-to-face courses (Lee & Choi, 2011; Sun & Rueda, 2012). Statistics show that it is particularly challenging for students who are unprepared to take online courses. In 2018, 85% of online students reported that their online learning experiences were the same or better than in-person courses, while during the 2020 pandemic, which forced students into online classes, 63% of students reported that online learning was worse than in-person

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learning (Education Data Initiative, 2020). This highlights the importance of providing guidance and scaffolding to learners without appropriate online learning skills.

Self-regulation is a critical skill required for successful online learning because students must manage their learning without an instructor's constant guidance (Kizilcec et al., 2017; Lee et al., 2019). Recently, growing interest in multimodal learning analytics has led researchers to develop innovative ways of assessing online learners' self-regulated behaviors and providing immediate guidance. This report introduces the use of an electroencephalography (EEG) device for collecting online learners' physiological information as multimodal data. We also discuss the use of a neurofeedback mechanism to provide immediate visual feedback to optimize online learners' self-regulated behaviors.

2 Description of the Emerging Technology

Neurofeedback is a mechanism for the operant conditioning of brain functions to modify behavior. The origin of neurofeedback dates back to the 1930s and 40s when it was discovered that subjects could operantly condition certain aspects of their brain waves (Jasper & Shagass, 1941). Although the theory behind neurofeedback has been known for decades, it has become increasingly relevant to educational research over the past few years because of recent technological advances reducing the barriers to the development of low-cost, high-quality portable EEG devices needed for neurofeedback.

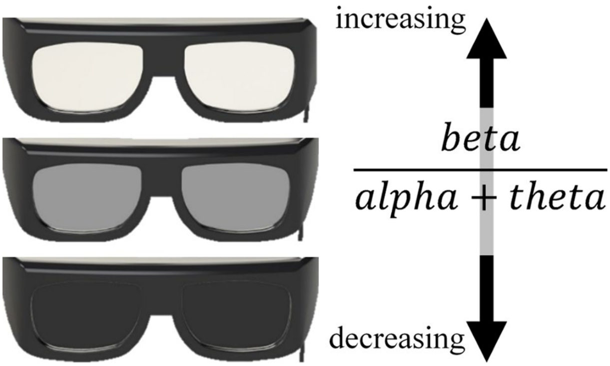
Although neurofeedback can be achieved in many ways, a typical application involves real-time EEG recordings made from the subject's scalp, which is by far the most common input for neurofeedback systems such as functional MRI, functional near-infrared spectroscopy, and electrocorticograms (Rieke et al., 2020). These brain waves pass through a signal-processing engine that quantifies the presence of desired and undesired signals. The actual signals of interest depend on the specific neurofeedback protocol and the behaviors it seeks to modulate. The user is incentivized to produce the desired neural patterns by presenting rewards such as an auditory tone or visual stimulus.

Based on this neurofeedback mechanism, Narbis, Inc. (Ambler, PA, USA) pioneered a device that provides neurofeedback brain training with immediate visual feedback to enhance concentration. The initial development was expanded to include a unique design, allowing use while performing other tasks in a non-intrusive manner (see Fig. 1). The glasses can be worn as regular glasses with a single dry EEG electrode that contacts the scalp and connects to a custom AC-coupled amplifier built directly into the electrode arm. The sampled and amplified signal is passed via Bluetooth to a dedicated Android-based tablet computer, which compares it with the criterion signal to determine the user concentration level. If the trend reveals decreasing user engagement, then a return signal is passed back to the processing unit, which causes the lenses to become progressively darker.

By contrast, increased engagement is rewarded with progressively more transparent lenses (see Fig. 2). The slowly darkening lenses gently provokes users to refocus their minds. This process may occur subconsciously, because neuroplasticity does not require active user engagement.

Fig. 1 Narbis system [left]; A typical use case [center]; a dry electrode [right, top]; a custom AC-coupled active amplifier [right, bottom]

Fig. 2 The change of brightness of the lenses depending on concentration levels



3 Relevance for Learning, Instruction, and Assessment

To support self-regulated learning, previous studies have incorporated self-regulation prompts (Manganello et al., 2019) or developed online modules that explicitly teach self-regulation strategies (Briscoe & Brown, 2019). However, these interventions are not designed to directly support student attention and concentration maintenance. Using an EEG device, concentration levels can be assessed, and neurofeedback can support online learners' maintenance of concentration in real time when used alongside learning analytics.

Learning analytics refers to "the measurement, collection, analysis, and reporting of data about learners and their contexts for the purposes of understanding and optimizing learning and the environments in which it occurs" (Siemens & Long, 2011, p. 34). It has gained tremendous attention as a method for improving data-driven instructional decision making (Ifenthaler, 2017; Picciano, 2012). With the affordability of online learning management systems that automatically collect massive amounts of large-scale data, many researchers have used learner-generated data to predict outcomes (Junco & Clem, 2015; Kew & Tasir, 2022) and have helped educators understand learners' behavioral patterns and optimize learning environments (Drachsler & Kalz, 2016). In addition to behavioral data, studies have indicated that multimodal data generated from sensor-based technologies can be more accurate in forecasting student performance (Emerson et al., 2020; Sharma et al., 2019).

However, the use of multiple data sources for learning analytics remains in its infancy and researchers have called for studies using more biometric sensor data (Bodily & Verbert, 2017).

Multimodal learning analytics using EEG can accurately assess learner self-regulation. Traditional self-report measures have been criticized for their lack of reliability and accuracy (Bannert et al., 2014). To overcome the limitations of self-reports, eye-tracking devices are often utilized to measure visual attention (e.g., Flynn et al., 2019; Vraga et al., 2016), but they only track gaze and do not capture the concentration level while engaging in visual stimuli. An EEG neurofeedback device can capture neural data representing learners' live concentration levels (Chen & Wu, 2015), which play an important role when learners perform learning tasks while monitoring their progress and using various self-control strategies to accomplish a task (Zimmerman, 2000). Therefore, it is essential to assess online learners' concentration during live performances. The Narbis neurofeedback device can be used for this purpose, and online learners' live neurosignals can be collected unobtrusively.

Furthermore, using cluster analysis, cohorts of online learners with similar backgrounds, characteristics, and initial concentration levels have been identified. Cluster analysis is a common method used in learning analytics research to create student learning profiles (Kim et al., 2018; Martín-Monje et al., 2018). Martín-Monje et al. (2018) collected behavioral data from students while interacting with instructional materials in massive online courses. They analyzed the data to classify students into different engagement styles. Based on student responses to self-regulated learning surveys, Kim et al. (2018) identified three self-regulated learning profiles in asynchronous online courses and examined the learning patterns of the three clusters. These student profiles can be used to design optimal instructional support.

Physiological information collected using the Narbis neurofeedback device can be used to create a student profile in a similar vein. These learner cohorts with similar profiles allow us to examine their self-regulated behaviors when engaging in different online learning tasks. For instance, multimedia learning materials include various sensory stimuli that activate involuntary attention more efficiently than text alone (Kaplan & Berman, 2010). Such attention is sustained differently depending on the design of the multimedia learning materials and learners' learning styles (Chen & Wu, 2015), which demands further examination of learners' self-regulation during online learning. Moreover, reading texts on screen generates distinct reading behaviors such as selective reading, including scanning, keyword spotting, and nonlinear reading, and less in-depth and concentrated reading, which is also associated with decreasing sustained attention (Liu, 2005). This result was further supported by neurobiological evidence showing reduced focused attention during screen-based reading (Zivan et al., 2023). Considering these previous results, online learners may need additional support during learning, which depends on the activities they are engaged in. For example, asynchronous discussions require much reading on screen and may demand more mental effort for students to concentrate compared to watching video lectures. Therefore, learners in need of neuropsychological and learning support can be identified based on their profiles and learning contexts.

In addition to identifying learners in need, neurofeedback devices can be further used to improve online learners' concentration. Neurofeedback has been shown to modify brain activity and mitigate undesirable behaviors (Jasper & Shagass, 1941; Jeunet et al., 2019). The specific mechanism of neural modification is likely operant conditioning, achieved through a combination of classical Hebbian learning counterbalanced by non-Hebbian homeostatic plasticity (Enriquez-Geppert et al., 2019; Sitaram et al., 2017). Meanwhile, various machine-learning algorithms have been used for educational purposes to forecast students' learning performance (Kotsiantis, 2012; Yağcı, 2022) and to support academic decision-making (Nieto et al., 2019). Consequently, we hypothesized that real-time brain training could be improved using machine learning to customize feedback for individuals or cohorts based on specific needs or deficits. As learners' abilities to control their engagement and concentration improve over time, they are forced to exhibit a deeper level of focus. Thus, the learner is subconsciously incentivized to develop the desired brain activity, which eventually improves concentration and self-regulation during online learning.

4 Emerging Technology in Practice

Neurofeedback has been applied in numerous areas ranging from behavioral modification to performance training to enhance athletic or surgical skills (Jeunet et al., 2019). Many studies have proven the effectiveness of neurofeedback in promoting focus and impulse control in children diagnosed with attention deficit hyperactivity disorder (ADHD) (e.g., Pakdaman et al., 2018). The Narbis neurofeedback system was developed and field-tested to demonstrate the enhancement of concentration (Orlandi & Greco, 2005). Although neurofeedback has been evaluated in limited educational contexts, neurofeedback training using easy-to-use and non-obtrusive devices has the potential to expand into a wider learner population. Moreover, with the increasing expectations of using multimodal data (Emerson et al., 2020) and their infancy in practical applications (Bodily & Verbert, 2017), the use of neurofeedback devices can provide a new way of collecting learner data for optimal support.

5 Significant Challenges and Conclusions

As with common concerns about learning analytics (Viberg et al., 2018), collecting neural data in online environments entails ethical issues such as data privacy, security, and informed consent, which researchers must pay close attention to. In addition, learners may find the neurofeedback headset physically cumbersome and the visual feedback distracting or ineffective. Although neurofeedback has been used to enhance focus and concentration in groups as diverse as pilots, astronauts, athletes, and children with ADHD, its application as a general-purpose tool in online education is novel. Future studies examining the use of neurofeedback in a wider range of educational settings will present significant advancements in the study of neurofeedback and yield best practices that will inform future research and industry development.

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Data and/or Code Availability Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Declarations

Competing interests Iyad Obeid serves as a consultant for Narbis, Inc.

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