Received: 17 May 2024 | Accepted: 11 November 2024

DOI: 10.1002/rev3.70020

STATE OF THE ART REVIEW

Review of Education BERA

Electroencephalography in naturalistic and semi-naturalistic educational contexts: A systematic review

Alfonso García-Monge[1] | **Henar Rodríguez-Navarro**[2] | **Daniel Bores-García**[3] | **Gustavo González-Calvo**[1]

[1]Departamento de Didáctica de la Expresión Musical, Plástica y Corporal (Research Group Embodied Education), Universidad de Valladolid, Valladolid, Spain

[2]Departamento de Pedagogía (Research Group Embodied Education), Universidad de Valladolid, Valladolid, Spain

[3]Departamento de Fisioterapia, Terapia Ocupacional, Rehabilitación y Medicina Física (Research Group Embodied Education), Universidad Rey Juan Carlos, Alcorcón, Spain

Correspondence
Gustavo González-Calvo, Departamento de Didáctica de la Expresión Musical, Plástica y Corporal, Facultad de Educación de Palencia, Universidad de Valladolid, Avenida de Madrid, 44. 34004, Palencia, Spain.
Email: gustavo.gonzalez@uva.es

Abstract

This systematic review examines 76 studies that have utilised portable electroencephalographic (EEG) devices in naturalistic and semi-naturalistic contexts. The review considers themes, purposes, contexts, application populations, device characteristics, and data use. The results show a dominance of studies focused on attention, in technology-mediated semi-naturalistic situations, in which records are made individually, with university students using low-cost equipment with fewer than 15 channels. This review highlights an emerging field within educational research that has not yet been fully integrated into educational practice. However, these first experiences can gradually generate a body of knowledge that will facilitate future applications, together with the development of better and more accessible devices. The use of these devices in educational contexts raises ethical concerns, particularly the influence on teaching decisions by opaque commercial algorithms that may oversimplify assessments of specific cognitive processes and fail to adapt to individual student characteristics.

KEYWORDS

educational technologies, electroencephalography, neuro information systems, neurophysiological measurements in education

Context and implications

Rationale for this study: Portable EEG devices are emerging tools that offer new insights into cognitive processes in learning situations.

Why the new findings are important: The findings of this study demonstrate the potential of EEG to monitor aspects such as attention and cognitive load in real time, which could enhance the personalisation of educational strategies.

Implications for educators, researchers and policy makers: This study has implications for educators, researchers and policy makers, as it illustrates how neurotechnology can be integrated into educational settings and emphasises the need for more naturalistic studies to maximise its impact. It also highlights the ethical challenges associated with the use of commercial algorithms in educational decision-making.

INTRODUCTION

At the World Economic Forum Davos2023, Nita A. Farahany (2023) presented the possibilities and challenges to be faced in the 'neuro-society'. As the sales of commercial devices based on electroencephalographic (EEG) readings to promote relaxation, focus or attention have become more popular, expectations regarding their use in areas such as marketing, video games or education have increased. In various fields, there is a growing interest in the use of EEG (Yao et al., 2022). In the last two decades, new EEG devices have made it possible for studies on brain activity to move beyond the laboratory, giving rise to new possibilities, speculations and potential scenarios.

Given the situated and culturally constructed nature of learning (e.g., Anderson et al., 1996; Brown et al., 1989), there has been a great expectation in the educational field about applying neuro-information systems in real-world contexts.

But beyond the potential application of these neuroimaging techniques in educational contexts and the expectations they generate, it is worth asking about the current level of maturity in the application of these devices in educational practice and analysing the limitations and challenges faced in the incorporation of this technology.

The potential of neuroscientific research in the classroom and its problems have been debated for some time (Fischer et al., 2007; Posner & Rothbart, 2007). Davidesco (2020) summarised this debate when he pointed out:

> Bridging neuroscience and education is challenging, because these disciplines have very different goals and research traditions. Neuroscientists typically adopt a reductionist approach and study cognitive functions in isolation. Educational researchers, on the other hand, focus on the learner as a whole and how the learner is embedded in a context, such as a classroom.

To bridge the gap between laboratory studies and educational practice, various neuroimaging techniques have been employed, each with its own advantages and limitations. For instance, techniques with high spatial resolution, such as functional magnetic resonance imaging (fMRI), allow for the observation of neuronal activity in deep brain structures. fMRI measures changes in cerebral blood flow, which enables the identification of brain areas activated during specific cognitive tasks. However, this technique has significant limitations:

it requires large, expensive equipment, highly controlled experimental procedures, and demands that participants remain still during the measurements (Seghier et al., 2019).

In contrast, functional near-infrared spectroscopy (fNIRS) is another neuroimaging technique that, although offering lower spatial resolution compared to fMRI, provides greater flexibility in educational settings. fNIRS measures changes in the concentration of oxyhaemoglobin and deoxyhaemoglobin in cortical brain regions, allowing for the non-invasive inference of neuronal activity using portable equipment. While this technique does not enable the observation of deep brain structures, it offers the advantage of being more accessible and less restrictive, as participants can move naturally during tasks, making it suitable for studies in more dynamic environments such as classrooms (Scholkmann et al., 2014). These characteristics have contributed to its increased use in educational contexts over the past decade (Zhan et al., 2024).

Another technique is electroencephalography (EEG). This method measures electrical activity in the cortex. EEG activity is recorded as voltage differences at various locations on the scalp, representing the summation of postsynaptic potentials from groups of neurons in the cortex. Until now, the study through EEG of the processes involved in learning in laboratory conditions has given productive results for their understanding (Tinga et al., 2020). However, the potential of the new wireless EEG devices, the incipient studies in educational, commercial or artistic fields, or the advertising of the companies that market them, have generated many expectations in researchers and educators; notwithstanding, in comparison with fields such as marketing (Bazzani et al., 2020) or video games (e.g., Ninaus et al., 2014; Vasiljevic & de Miranda, 2020), research is still limited.

The high temporal resolution, non-invasiveness, the large amount of information it provides about different neural processes, and its portability suggest that the EEG is a very attractive procedure for educational research and as an aid to teachers and students. However, its use in real contexts is conditioned by its characteristics. The signals are highly prone to motion artefacts, for example, when blinking, speaking or moving the head (common movements in educational situations). Additionally, the cost of each device is based on its quality, marked by the number of sensors, their technical characteristics (active or passive, contact or with a conductive substance), and the sampling rate or the amplifier for sending the signal to the receiving computer. The worse the signal or the fewer recording channels used, the less validity the results will have and processes such as source modelling may be less accurate, as well as the removal of artefacts through processes such as linear regression or adaptive filtering (Chavez et al., 2018) or blind source separation (Jung et al., 2000) that require several reference channels. Depending on the quality, costs can range from $100 to $25,000. This is important because it establishes a tension between the quality of the records and the possibility of having several devices to collect simultaneous information from several students in an educational context (García-Monge et al., 2023).

Conducting neuroscience studies in naturalistic educational environments presents several challenges. Naturalistic stimuli, such as films, narratives or real-world interactions, introduce complexities that are less controlled compared to traditional laboratory settings. These stimuli mimic everyday life, allowing for a more ecologically valid representation of brain function, but they also introduce methodological difficulties, such as controlling for variability in individual engagement and environmental factors (Sonkusare et al., 2019). Additionally, naturalistic paradigms require advanced analytical approaches to account for the dynamic and multimodal nature of the stimuli. Despite these challenges, naturalistic stimuli are crucial for understanding how brain processes unfold in real-world scenarios and can yield insights into how students process information in educational contexts (Willems et al., 2020). The works of Janssen et al. (2021) or van Atteveldt et al. (2018) show several examples of the EEG potential in education. Neurophysiology can help psychologists and educators gain a deeper understanding of cognition, motivation or the effects of different tasks, overcoming some limitations of rating scales and allowing access to internal processes (Murphy & Benton, 2010), helping to understand individual processes and detect problems (e.g., Vandermosten et al., 2016), or generating neurofeedback procedures that provide feedback for learning and promote metacognitive processes (e.g., Hall & Johansson, 2003). On the neuroscience side, work in educational settings can generate new questions and lines of research (Willingham, 2009).

A non-systematic review on the use of EEG devices in educational contexts can be seen in Xu and Zhong (2018), although they leave out fundamental works (e.g., Dikker et al., 2017), as well as studies from the last 6 years, important for understanding the possibilities of neuroscientific research in school classrooms (e.g., Bevilacqua et al., 2019; Xu et al., 2022). This article provides a systematic review of the studies from the last 10 years on the use of EEG in educational contexts. Starting from the generic question "How is EEG technology used in semi-naturalistic and naturalistic educational contexts?", the scope of this review is guided by the following specific research questions: (1) What topics are addressed? (2) What purposes are pursued? (3) In what contexts are the studies carried out? (4) With what kind of participants are these experiences developed? (5) What kind of devices are used? (6) How are data obtained from the EEG devices used?

The discussion of the results will allow us to analyse the degree of maturity of this technology applied to education, as well as its limitations and challenges.

METHOD

Search sources

A systematic review was conducted of the literature published on EEG in the educational context. In order to find existing publications, a search was initiated in the electronic database Scopus. It was subsequently expanded through ScienceDirect and supplemented through the snowballing approach (Jalali & Wohlin, 2012; Webster & Watson, 2002). It was decided to use these complementary sources since in the review process we noticed that many contributions on this topic come from the engineering field and their findings are usually reflected in conference proceedings. Descriptors "EEG school", "EEG education", "EEG learning", "EEG students" and "EEG children" were used. The search was conducted between June 2022 and May 2023, covering 10 years of publications (2013–2023).

Exclusion criteria

The selection of articles referring to experiences in naturalistic and semi-naturalistic contexts, as defined by Matusz et al. (2019), was established as a basic criterion. There are intermediate steps between pure laboratory conditions and those of ordinary social practices that have been explored in the last decade. Matusz et al. (2019) propose three categories to define research approaches with respect to the degree of "naturalism": controlled laboratory, partially naturalistic laboratory (semi-naturalistic) and naturalistic real-world research (a more detailed development of this classification can be found in Naumann et al., 2022). For Janssen et al. (2021), these three approaches can be seen as a three-stage cyclical model for educational neuroscience in which lab studies are needed to provide a basis for more naturalistic research, with the latter providing ground for previously established knowledge or for formulating new hypotheses that can be tested in more controlled lab or semi-naturalistic environments. Just as a pure laboratory situation designs experiments so that stimuli demand only one form of cognitive processing (Han et al., 2019), semi-naturalistic situations would introduce more open-ended and multisensory stimuli, close to everyday situations. In the case of naturalistic situations, neuroimaging devices would be introduced into everyday contexts in which events are not so predetermined and interactions demand continuous and complex experiences.

From this basic categorization, the exclusion criteria used were as follows: (1) Duplicated articles, (2) Studies that did not use EEG devices, (3) Articles about proposals that did not specify data on their development (did not specify sample, procedure or results), (4) Studies with laboratory or therapeutic procedures, and (5) Studies that lacked a semi-naturalistic or naturalistic character in educational contexts and with mainstream student populations.

For example, interesting articles were rejected that, despite trying to reproduce semi-naturalistic situations, did not use educational materials in their development, but rather standardised laboratory tests (e.g., Apicella et al., 2022; Li et al., 2022), or researches that using educational materials were developed in special laboratory conditions (e.g., the work of Choi et al., 2019, studies the variations in reading attention as a function of temperature changes within a climate chamber). Several papers utilized resting-state procedures before and after academic tasks to examine potential changes in brain activity (e.g., Rajendran et al., 2022; Siripornpanich et al., 2018). Additionally, other studies employed experimental protocols that were not designed to replicate real-world learning scenarios, focusing instead on controlled conditions to investigate specific cognitive or neural mechanisms (e.g., Daly et al., 2019). Those studies not focused in some way on teaching and learning, which use recreational materials, have also been discarded (e.g., such as the one by Kavitha et al., 2023, which used entertainment videos, songs, dances or magic shows to analyse the emotional state of the students). Likewise, those studies not developed with mainstream student populations were rejected (e.g., Waisman et al., 2023). Studies that aimed to develop classifiers for different functions involved in learning processes but relied on databases to train them were also excluded (e.g., Al-Nafjan & Aldayel, 2022; Nandi et al., 2021).

Search limits and procedure

The search was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher, Liberati, Tetzlaff, & Altman, 2009). The search ended on May 20, 2023. Figure 1 shows the process from the beginning of the search in the databases to the selection of the final 76 articles that comprise this systematic review.

After the first search, through reading the titles and the abstracts, articles that did not meet criteria 1, 2, 4 and 5 were rejected, that is: duplicates; those that did not use EEG technology; those whose title and abstract made it clear that they were not related to educational contexts; those referring to laboratory conditions and therapeutic procedures; and those that did not refer to mainstream student populations. In those articles that did not make clear in their abstract the data on the participants, the procedures or the results, the body of the text was searched for these data. In a final screening, those articles not referring to naturalistic or semi-naturalistic educational situations or in which educational materials were not used were rejected. The first and last author jointly conducted the screening, data extraction and data synthesis processes. Cases of uncertainty were reviewed by all four authors, and consensus was reached.

The selected articles were finally read by all the researchers and the information was extracted in the words of the authors. The basic information was entered into a table in

"EEG school"	"EEG education"	"EEG learning"	"EEG students"	"EEG children"
Scopus: 2,100	Scopus: 1,112	Scopus: 12,950	Scopus: 2,256	Scopus: 7,839

Search on Science Direct database and snowballing approach: 101,820

Total number of initial articles: **128,077**

Articles excluded:

(1) Duplicate articles: 43,560
(2) Articles that did not use EEG devices: 7,431
(3) Articles on proposals that did not specify data on their development (did not specify sample, procedure or results): 12,328
(4) Studies with laboratory or therapeutic procedures: 28,641
(5) Studies that lacked a semi-naturalistic or naturalistic character in educational contexts and with mainstream student populations: 36,041

Final search: **76**

FIGURE 1 Flow diagram of the systematic search process.

which basic data were collected to guide the answer to the research questions: (1) Authors and date; (2) Topic; (3) Characteristics of the data collection, context and participants; (4) Procedure; (5) Characteristics of the EEG devices used; (6) Signal processing and data analysis.

RESULTS

Considering the results shown in Table 1 and in the Sankey diagram shown in Figure 2, it could be summarized that most of the studies focused on attention, in semi-naturalistic technology-mediated situations, in which records were made individually with university students through low-cost equipment, with less than 15 channels.

What topics are covered?

Most of the articles focus on the study of two highly related topics: attention ($n=39$, 51.3%) and engagement ($n=13$, 17.1%). This assessment of attention or engagement occurs in varied contexts and with diverse populations. We found research on attention or engagement during reading tasks (e.g., Huang et al., 2014), during the follow-up of educational videos (e.g., Lee & Chin, 2014), in the practice of educational games in 3D environments (e.g., Ghali et al., 2016), valuing attention in affective tutoring systems (Lin et al., 2016), in monitoring both online (e.g., Chen & Wang, 2017) and face-to-face classes (e.g., Sezer et al., 2017), effects of environment and posture (Kim et al., 2020; Yang et al., 2020), noting the effects on attention or engagement before short stimuli of less than 6 minutes (e.g., Poulsen et al., 2017) or carrying out prolonged follow-ups during the school day (Dikker et al., 2020). Related to attention, two programmes to improve mindfulness through neurofeedback provided by an EEG-based application are also included (Martinez & Zhao, 2018; Vekety et al., 2022). Some of these studies have identified neural patterns that correlate with attention, suggesting that EEG could be a valuable tool for monitoring engagement in real time and adjusting teaching strategies accordingly.

Regarding the studies on attention and engagement, 54% ($n=27$) were measured through the algorithm of the application associated with the EEG device used.

The third most researched topic (9.4%) is the cognitive load caused by reading situations (Baceviciute et al., 2021), in watching videos (Zhou et al., 2017), during problem solving

TABLE 1 EEG studies in educational contexts.

Authors	Topic	Sample-participants	Device	Signal processing and data analysis
Liu et al. (2013)	Attention monitoring during the online class	24 university students (age: 22–27) Individual record. Semi-naturalistic situation	EEG 1 channel (512 Hz, NeuroSky)	Continuous signal segmentation. Feature extraction from different frequencies. Classification through different supervised machine learning methods
Chen and Lin (2016)	Effects of different text display types on reading comprehension, sustained attention and cognitive load in mobile reading contexts	20 university students (age: 23–26) Individual record. Semi-naturalistic situation	EEG 1 channel (512 Hz, NeuroSky)	Device app algorithm
Huang et al. (2014)	BCI system to detect reading engagement	20 schoolchildren (age: 7–8). Individual record. Semi-naturalistic situation	EEG 14 channels (128 Hz, Emotiv Epoc)	Estimation of engagement based on the correlate: beta/ alpha+theta
Lee and Chin (2014)	Evaluation of a BCI system to improve engagement with educational videos	20 kindergarten kids (age: 4–6) to adjust the system Brainwave Educator Assistant and 40 (4–6) to test it in semi-naturalistic situations	EEG 14 channels (128 Hz Emotiv Epoc)	Classification from Power Spectral Density (PSD) of beta (parietal and frontal)/ alpha+theta occipital
Sun (2014)	Assessment of student engagement and attention	32 university students Simultaneous record. Naturalistic situation	EEG 1 channel (512 Hz, NeuroSky)	Device app algorithm
Mazher et al. (2015)	Comparison of cognitive load during learning through multimedia animations	5 university students (age: 18–30) Individual record. Semi-naturalistic situation	EEG 128 channels (250 Hz, EGI EEG)	PSD extraction for alpha waves of each channel and comparison between brain regions
Verkijika and De Wet (2015)	Using a BCI in reducing math anxiety	36 schoolchildren (age: 9–16) Individual record. Semi-naturalistic situation	EEG 14 channels (128 Hz, Emotiv Epoc)	A BCI mathematics educational game called Math-Mind was developed by the researchers. The participants played the game while wearing the BCI headset. The Math-Mind game captured real-time brain activity with the Emotiv EPOC BCI and provides visual feedback to the user when anxiety levels rise

(Continues)

TABLE 1 (Continued)

Authors	Topic	Sample-participants	Device	Signal processing and data analysis
Ghali et al. (2016)	Engagement and motivation during the practice of an educational game in a 3D environment (chemistry lesson)	40 university students (age: 19–35) Individual record. Semi-naturalistic situation	EEG 14 channels (128 Hz, Emotiv Epoc)	Device app algorithm
Ghergulescu and Muntean (2016)	Engagement and motivation in game-based e-learning	50 university students (age: 18–55). Individual record. Semi-naturalistic situation	EEG 14 channels (128 Hz, Emotiv Epoc)	Device app algorithm
Lai et al. (2016)	Assessment of the effects of using feedback to learner responses through images as a function of EEG (attention) recording in online learning	42 students (age: 16–20) Individual record. Semi-naturalistic situation	EEG 1 channel (512 Hz, NeuroSky)	Device app algorithm
Lin et al. (2016)	EEG as feedback support to detect attention-relaxation states and introduce neurofeedback in the follow-up of a lesson	78 university students Individual record. Semi-naturalistic situation	EEG 1 channel (512 Hz, NeuroSky)	Device app algorithm
Chen and Wang (2017)	Attention monitoring in an online course	148 students (age: 12–13) Individual record. Semi-naturalistic situation	EEG 1 channel (512 Hz, NeuroSky)	Use of neurofeedback application
Dikker et al. (2017)	Teacher-student and student–student brain synchrony	12 students (age: 16–18) Simultaneous record Naturalistic situation	EEG 14 channels (128 Hz, Emotiv Epoc)	Continuous signal segmentation. Calculation of spectral coherence between channels (minimum of 30 segments) and between participants (in 6 channels)
Huang et al. (2017)	Display of images as a reward for student responses. EEG is used to detect the level of attention of students	44 university students (age: 19–21) Individual record. Semi-naturalistic situation	EEG 1 channel (512 Hz, NeuroSky)	Device app algorithm

TABLE 1 (Continued)

Authors	Topic	Sample-participants	Device	Signal processing and data analysis
Hu and Kuo (2017)	Assessment of engagement by viewing different educational videos	8 university students (age: 20–43) Individual record. Semi-naturalistic situation	EEG 5 channels (128 Hz Emotiv Insight)	Power Spectral Density (PSD) calculation in different frequency bands. Classification to guide the adjustment of teaching methods and materials
Ko et al. (2017)	Evolution of attention throughout the lecture by studying the spectral powers in different frequency bands	18 university students (age: 23–27) Simultaneous record Naturalistic situation	EEG 32 channels (1000 Hz, NeuroSkan)	Continuous signal segmentation. Investigation of spectral characteristics
Moldovan et al. (2017)	Student interest in multimedia-based mobile learning and reading texts of Russian literature	60 university students (age: 20–53) Individual record. Semi-naturalistic situation	EEG 14 channels (128 Hz, Emotiv)	Device app algorithm for engagement, frustration, meditation and emotion detection
Poulsen et al. (2017)	Synchronised neural recordings during video presentation	42 university students (age: 22). Registros simultáneos Naturalistic situation	EEG 14 channels (128 Hz, Emotiv Epoc)	Correlational component analysis to find synchronicity
Sezer et al. (2017)	Levels of attention during a class with student participation	21 university students Registros simultáneos (age: 21) Naturalistic situation	EEG 1 channel (512 Hz, NeuroSky)	Device app algorithm
Sun and Yeh (2017)	Improving attention with EEG biofeedback during text reading	80 university students (age: 23.5) Individual record. Semi-naturalistic situation	EEG 1 channel (512 Hz, NeuroSky)	Device app algorithm
Zhou et al. (2017)	Workload monitoring in the work of an online environment (MOOC) through a BCI system	University students. Individual record. Semi-naturalistic situation	EEG 14 channels (128 Hz, Emotiv Epoc)	Signal classifier (SVM) using signal power features and statistical theta and alpha features (channels F3 and F4)
Cohen et al. (2018)	Attention paid to different videos	39 university students Individual record. Semi-naturalistic situation	EEG 64 channels (512 Hz, BioSemi)	Correlation between subjects with more informative characteristics

(Continues)

TABLE 1 (Continued)

Authors	Topic	Sample-participants	Device	Signal processing and data analysis
Dan and Reiner (2018)	To compare cognitive load in 2 virtual learning scenarios—on 2D displays and with an identical 3DS scenario	14 university students (age: 21–40) Individual record. Semi-naturalistic situation	EEG 20 channels (2000 Hz, Mitsar)	Analysis of the recorded signals to build a power spectra density curve. The calculation of the cognitive load was done with the Theta ratio. (Fz)/Alpha (Pz)
Lin and Kao (2018)	Development of a system for monitoring and labelling mental effort in online learning situations	32 university students (age: 22–33) Individual record. Semi-naturalistic situation	EEG 1 channel (512 Hz, NeuroSky)	Continuous signal segmentation. Feature extraction from different frequencies. Classification through different supervised machine learning methods
Martinez and Zhao (2018)	Behavioural improvement programme through mindfulness	9 students (age: 12–14) Paired registration Semi-naturalistic situation	EEG 4 channels (250 Hz, Muse)	Using EEG with a feedback app for relaxation
Meza et al. (2018)	To study the feasibility of a tool that allows an estimate of the attention status of a person, in order to train and improve future activity in the spectrum of a child's school environment	University students. Individual record. Semi-naturalistic situation	EEG 3 channels (256 Hz, OpenBCI)	Filtering the Beta signal by Wavelet Development of a classifier
Mohamed et al. (2018)	Development of an attention and working memory classifier from EEG signals	86 university students (age: 18–23) Individual record. Semi-naturalistic situation	EEG 14 channels (128 Hz, Emotiv epoc)	Feature extraction and classification using various ML procedures
Sethi et al. (2018)	Effect of real-time attention based neurofeedback on a reading comprehension task	41 university students (age: 18–21) Individual record. Semi-naturalistic situation	EEG 1 channel (512 Hz, NeuroSky)	Device app algorithm
Antonenko et al. (2019)	Synchrony of mutually interacting brains, or team neurosynchrony, during cyber-enabled collaborative problem solving	140 university students (age: 18–24) Individual record. Semi-naturalistic situation	EEG 9 channels (250 Hz, B-Alert X-10)	Alpha-band phase-locking value, or the absolute value of the sum of the phase differences of electrodes at a particular time and frequency across a number of epochs, was used as a measure of team neurosynchrony

TABLE 1 (Continued)

Authors	Topic	Sample-participants	Device	Signal processing and data analysis
Babiker et al. (2019)	Detecting situational engagement using EEG in classroom	43 university students Simultaneous record Naturalistic situation	EEG 8 channels (500 Hz, Enobio	Situation segmentation. Frequency band feature extraction and classification through Support Vector Machine and K-Nearest Neighbour
Bevilacqua et al. (2019)	Teacher-student and student–student brain synchrony	12 students (age: 16–18) Simultaneous record. Naturalistic situation	EEG 14 channels (128 Hz, Emotiv Epoc)	Continuous signal segmentation. Calculation of spectral coherence between channels (minimum of 30 segments) and between participants (in 6 channels)
Eldenfria and Al-Samarraie (2019)	The quantitative EEG was used to analyse the brain activation of students while learning using an Online Continuous Adaptation Mechanism	41 university students (20–25) Individual record. Semi-naturalistic situation	EEG 14 channels (128 Hz, Emotiv Epoc)	Calculation of different ratios between frequency bands: Arousal (Beta/Alpha ratio), Concentration (SMR + Beta/Theta), Engagement (Beta/Alpha+Theta)
Khedher et al. (2019)	Assessment of engagement and cognitive load	15 university students Individual record. Semi-naturalistic situation	EEG 14 channels (128 Hz, Emotiv Epoc)	Continuous signal segmentation. PSD calculation. Application of the ratio beta/theta+alfa
Kosmyna and Maes (2019)	Improvement of the engagement through neurofeedback in learning situations (video lectures and face to face lectures with a professor)	12 university students (age: 21) Individual record. Semi-naturalistic situation	EEG 1 channel (Focus BrainCo)	Calculation of engagement index (Beta/Alpha+Theta)
Lai et al. (2019)	EEG to calculate attention and develop a model for the identification of students who are likely to fail in reading.	55 university students (age: 21–23) Individual record. Semi-naturalistic situation.	EEG 1 channel (512 Hz, NeuroSky)	Device app algorithm
Lin and Chen (2019)	Improving effectiveness of learners' review of video lectures by using an attention-based video lecture review mechanism based on EEG	55 children (third grade) Simultaneous record. Semi-naturalistic situation.	EEG 1 channel (512 Hz, NeuroSky)	Device app algorithm

(Continues)

TABLE 1 (Continued)

Authors	Topic	Sample-participants	Device	Signal processing and data analysis
Makransky et al. (2019)	Assessment of cognitive load in virtual context of science learning	52 university students (age: 19–42) Individual record. Semi-naturalistic situation	EEG 9 channels (256 Hz, ABM X-10)	Modelling technique that incorporates multiple EEG variables to be used as inputs to quadratic and linear discriminant function analyses that provide classifications for each second of EEG
Robinson et al. (2019)	Assessment of emotional climates in online teamwork with text-based communication (reading, thinking and writing)	12 students and professors (age: 25–65) Individual record. Semi-naturalistic situation	EEG 21 channels (256 Hz)	Segmentation of continuous signals. Calculation of average frequencies in channels F3, F4, T4 and T5 and statistical comparisons between conditions
Zhu et al. (2019)	Engagement with different MOOC presentation videos	15 university students (age: 18–25) Individual record. Semi-naturalistic situation	EEG 64 channels (1000 Hz, Compumedics NeuroScan)	Between-subjects correlated component analysis. Correlation between subjects for each video
Babiker et al. (2020)	Engagement to qualify students' interest based on their respective brain activities	30 university students Simultaneous record Naturalistic situation	EEG 8 channels (500 Hz, Enobio)	Artificial neural networks to discriminate the EEG data as relevant to either high or low situational from the classification of Approximate Entropy
Dikker et al. (2020)	Variations in alpha power and peak alpha throughout the school day	22 students (age: 17–18) Simultaneous record Naturalistic situation	EEG 14 channels (128 Hz, Emotiv epoc)	Segmentation of continuous data (occipital channels). Alpha power spectra and individual alpha frequency peaks
Hernandez-Cuevas et al. (2020)	Creation of feedback programmes by secondary school students	14 students (age: 16) Naturalistic situation	EEG 4 channels (220 Hz, Muse)	Creation of flow blocks for neurofeedback from PSD in different frequency bands

TABLE 1 (Continued)

Authors	Topic	Sample-participants	Device	Signal processing and data analysis
Kim et al. (2020)	To compare the concentration and emotional condition of elementary school students performing an intensive assignment in the presence or absence of foliage plants, using EEG	30 children (age: 10–13) Individual record. Semi-naturalistic situation	EEG 2 channel (Quick-20 Cognionics)	Spectral power of theta and beta bands
Kumari and Deb (2020)	Attention level of students inside the class	58 university students Simultaneous record. Naturalistic situation	EEG 1 channel (512 Hz, NeuroSky)	Device app algorithm
Ni et al. (2020)	Analysis of attention in learning in three learning media (text, text + graphic and video)	30 university students (age: 19–31) Individual record. Semi-naturalistic situation	EEG 1 channel (512 Hz, NeuroSky)	Device app algorithm
Shadiev and Huang (2020)	To compare student attention, meditation, cognitive load, and satisfaction during lectures in a foreign language supported by speech-enabled language translation	60 university students (age: 18–22) Simultaneous record. Semi-naturalistic situation	EEG 1 channel (512 Hz, NeuroSky)	Device app algorithm
Varnavsky and Romanova (2020)	Level of engagement to different texts through the analysis of Theta's Absolute Spectral Power	10 university students (age: 20) Individual record. Semi-naturalistic situation	EEG 32 channels (5000 Hz, Neuron-Spectrum)	Calculation of Absolute Spectral Power of Theta in FP1 and FP2
Wang et al. (2020)	Effects of instructor presence on learners' processing of information using both subjective and EEG measures of cognitive load	60 university students (age:18–27) Individual record. Semi-naturalistic situation	EEG 19 channels (300 Hz, DSI-24 EEG, Wearable Sensing)	Calculation of average power in alpha and theta and comparison between conditions.
Yang et al. (2020)	Effects of environment and posture on the concentration and achievement of students in mobile learning	120 university students (age: 20) Individual record. Semi-naturalistic situation	EEG 1 channel (512 Hz, NeuroSky)	Device app algorithm

(Continues)

TABLE 1 (Continued)

Authors	Topic	Sample-participants	Device	Signal processing and data analysis
Yu et al. (2020)	Construction of a signal classifier to monitor academic self-efficacy	39 university students Individual record. Semi-naturalistic situation	EEG 2 channels (512 Hz, BrainLink)	Signal classifier with a deep learning network
Aggarwal et al. (2021)	To assess attention levels of a learner in MOOC learning environments and compare it with conventional classroom learning using brain signals	12 university students (age:19–31) Individual record. Semi-naturalistic situation	EEG 1 channel (512 Hz, NeuroSky)	PSD and machine learning classification model of support vector machines (SVM) was used to classify student's mental state
Baceviciute et al. (2021)	Attention and reading workload in virtual environments	51 university students (age. 18–34) Individual record. Semi-naturalistic situation	EEG 9 channels (256 Hz, ABM X-10)	Comparison of PSD for different bands (theta, alpha and beta) under different conditions
Chen et al. (2021)	To explore the changes in learning attention and learning effectiveness of mobile learners in different presentation forms and interactive methods of learning resources, including plain text, video and interactive methods represented by dubbing	18 university students (age: 19–21) Individual record. Semi-naturalistic situation	EEG 1 channel (512 Hz, NeuroSky)	Device app algorithm
Grammer et al. (2021)	Variations in different frequencies according to attention states before different instructional activities (lecture, videos, discussion, etc.)	23 university students Individual record. Semi-naturalistic situation	EEG 24 channels (250 Hz, mBrainTrain)	Power of different frequencies of a segmented continuous signal
Pajk et al. (2021)	Monitoring the effectiveness of interdisciplinary STEM model using EEG and mobile applications. Online videos	20 university students (age: 18–20) Individual record. Semi-naturalistic situation	EEG 1 channel (512 Hz, NeuroSky)	Device app algorithm
Ramírez-Moreno et al. (2021)	Performance prediction in learning tasks (text and video) through a machine learning tool	20 university students (age. 22) Individual record. Semi-naturalistic situation	EEG 8 channels (256 Hz, OpenBCI)	Extraction of features from frequency bands. Creation of a classifier for use in semi-naturalistic contexts

TABLE 1 (Continued)

Authors	Topic	Sample-participants	Device	Signal processing and data analysis
Zhang et al. (2021)	Attention fluctuations in the context of video learning	18 university students (age: 24) for developing the classifier 24 university students (age: 23) for the test Individual record. Semi-naturalistic situation	EEG 1 channel (512 Hz, NeuroSky)	Feature extraction from frequency bands. Classification through SVM. Creation of a classifier for use in semi-naturalistic contexts
Bitner and Le (2022)	Assessment of sustained attention in a learning programming task	23 university students (age: 19–30) Individual record. Semi-naturalistic situation	EEG 1 channel (512 Hz, NeuroSky)	Comparison of PSD in different bands with Device app algorithm
Du et al. (2022)	Analyse the process of online collaborative problem solving via brain-to-brain synchrony at the problem-understanding and problem-solving stages	36 university students (age: 21) Simultaneous record Naturalistic situation	EEG 1 channel (512 Hz, BrainLink)	ThinkGear Asic signal analysis module that extracts power band values in delta, theta, low-alpha, high-alpha, low beta, high-beta, low-gamma, low-gamma, mid-gamma
Juan and Chen (2022)	To test the influences of indoor classroom setting on attention and learning	68 university students Individual record. Semi-naturalistic situations	EEG 1 channel (512 Hz, NeuroSky)	Device app algorithm
García-Monge et al. (2022)	Differences in attention between throwing games	8 schoolchildren (age: 7–8) Individual record. Semi-naturalistic situation	EEG 14 channels (128 Hz, Emotiv Epoc)	Continuous signal segmentation. Power Spectral Density (PSD) calculation in different frequency bands
Sorochinsky et al. (2022)	Analysis of the level of attention of trainees while watching an educational video with neurofeedback	20 university students (age: 21–24) Individual record. Semi-naturalistic situation	EEG 6 channels (125 Hz, OpenBCI)	Attention/concentration data calculated by the device's own software (based on beta and theta analysis in Fp1 and Fp2)
Sulaiman et al. (2022)	Classification of signals for monitoring students' attention	6 university students (age: 20–21) Individual record. Semi-naturalistic situation	EEG 1 channel (512 Hz, NeuroSky)	Characteristics extraction from different frequencies. Classification through supervised machine learning

(Continues)

TABLE 1 (Continued)

Authors	Topic	Sample-participants	Device	Signal processing and data analysis
Suttidee and Ruanguttamanun (2022)	Measuring attention in an online class	36 university students (age: 20) Individual record. Semi-naturalistic situation	EEG 1 channel (512 Hz, NeuroSky)	Cognitive effort pattern is mentioned but not specified as to how it is obtained.
Upadhyay et al. (2022)	Attention activity visualising different educational videos	20 students (age: 21) Individual record. Semi-naturalistic situation	EEG 20 channels (256 Hz, Allengers NeuroPLOT)	Comparative analysis of the frequency spectrum
Vekety et al. (2022)	Improvement of mindfulness and executive functions through a neurofeedback programme	31 schoolchildren (age: 8–12) Individual record. Semi-naturalistic situation	EEG 4 channels (250 Hz, Muse)	Using EEG with a feedback app for relaxation
Veronica et al. (2022)	Working memory in reading	23 students (age: 10–11) Individual record. Semi-naturalistic situation	EEG 4 channels (250 Hz, Muse)	Segmentation of continuous data. Alpha frequency spectral density
Xu et al. (2022)	Attention analysis	46 schoolchildren (age: 6–7) Records in trios Semi-naturalistic situation	EEG 24 channels (250 Hz, actiCAP BrainProducts)	Analysis of alpha frequency spectral density
Bouhdana et al. (2023)	Assessment of the engagement depending on the contextualisation of different physics problems	60 university students (age:23.7) Individual record. Semi-naturalistic situation	EEG 32 channels (ActiCap, BrainVision)	Calculation of cognitive engagement index (Beta/Alpha+Theta)
Davidesco et al. (2023)	Brain-to-brain synchrony between students and teachers and learning outcomes	31 university students (age: 18–30) Simultaneous record. Naturalistic situation	EEG 32 channels (500 Hz, Enobio)	Circular correlations were calculated for each pair of students and with the teacher
Garces-Gomez et al. (2023)	Emotional appraisal (arousal-valence) during the performance of a mathematics exam	4 university students. Individual record. Semi-naturalistic situation	EEG 16 channels (256 Hz, OpenBCI)	Spectral power maps for alpha and beta frequencies
Kim and Gero (2023)	EEG responses in virtual classrooms through measuring relative alpha and beta power using EEG in two different display conditions: a conventional computer display and an immersive VR Head-Mounted Display	17 university students (age: 21). Individual record. Semi-naturalistic situation	EEG 19 channels (300 Hz, DSI-24 W.S.)	Power Spectrum Analysis (PSA): Alpha and beta relative powers

TABLE 1 (Continued)

Authors	Topic	Sample-participants	Device	Signal processing and data analysis
Tang et al. (2023)	Attention to different in-class and online activities (lectures, tests, discussions)	36 university students (age:21) Simultaneous record Naturalistic situation	EEG 1 channel (512 Hz, BrainLink)	Attention indicators provided by the application through its own algorithms
Xiaojun et al. (2022)	Shared attention analysis using augmented reality	80 schoolchildren (age: 8–9) Paired records Semi-naturalistic situation	EEG 2 channels (512 Hz, BrainLink)	No signal processing. Device application data.
Zheng et al. (2023)	To investigate the effects of different types of cues and self-explanation prompts in instructional videos on intrinsic motivation, learning engagement, learning outcomes, and cognitive load, which were indicators to measure deep learning performance	72 university students (age: 18–25) Individual record. Semi-naturalistic situation	EEG 1 channel (512 Hz, NeuroSky)	Device app algorithm
Chen et al. (2023)	Inter-brain coupling in different disciplines (Math vs. Chinese) during real-world classroom learning	34 high school students (age: 15–16)	EEG headband (2 dry electrodes at Fp1/Fp2, 250 Hz, Brainno-soso)	Inter-brain coupling analysis using Total Interdependence (TI) method; analysis in theta, alpha, low-beta, and high-beta bands. Correlations with final exam scores for each discipline; permutation tests to verify findings

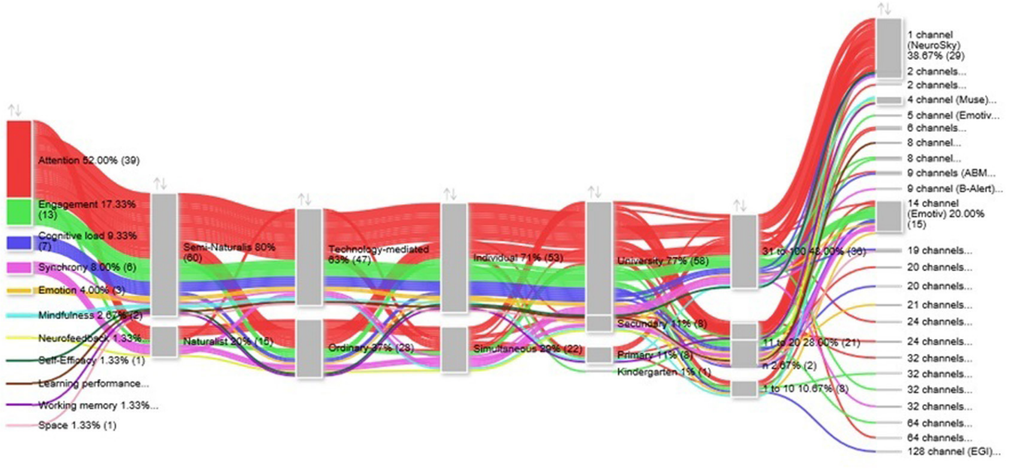

FIGURE 2 Sankey diagram relating the characteristics of the reviewed studies (subject, naturalism' grade, situation, participation, participants and number of the channels of the devices used).

(Khedher et al., 2019) or in the development of games in 3D environments (Makransky et al., 2019; Mazher et al., 2015). This cognitive load is estimated from power spectral density analysis procedures in different frequency bands (frontal theta power, the beta/theta+alpha ratio, Theta (Fz)/Alpha (Pz) ratio, comparison of alpha in different regions) and procedures for classifying signal characteristics through machine learning. By measuring cognitive load through EEG, researchers can determine when students feel overwhelmed and adjust teaching materials or methods to optimise information retention without causing excessive cognitive stress.

Research on synchrony and inter-brain coupling opens up new possibilities for applying these technologies to better understand communication and learning processes in naturalistic contexts. For instance, the pioneering work of Dikker et al. (2017) demonstrated that brain synchrony among students in a classroom predicts class engagement and social dynamics, and may be driven by shared attention within the group. The study by Bevilacqua et al. (2019) highlights interesting dynamics in educational processes: brain synchrony between teacher and student was greater during video-based lessons compared to lectures, yet teacher-student synchrony during lectures positively correlated with the perceived closeness between the teacher and students. Chen et al. (2023) found that students with higher scores on the final math exam exhibited stronger inter-brain coupling with the rest of their classmates, while students with higher scores in language showed stronger inter-brain coupling with the top-performing students in the class. These hyperscanning methods have also allowed for exploration into how synchrony or inter-brain coupling can predict learning outcomes (Davidesco et al., 2023).

Table 2 shows the rest of the topics, addressed to a lesser extent: emotions, working memory, self-efficacy, learning performance, or effects of space and on EEG activity.

Figure 3 shows a Sankey Diagram relating the topics studied and the types of devices used.

These lines of inquiry provide valuable insights into the cognitive processes underlying various educational situations, advancing the measurement of attention, cognitive load, interpersonal synchrony and the emotional implications of learning processes. The results suggest a potential educational impact, given the possible applications for designing curriculum materials better aligned with students' needs. However, as we will address in the discussion, their application in educational settings remains limited.

TABLE 2 EEG studies analysed grouped by topics.

Topic	Studies	Number
Attention	Liu et al. (2013), Chen and Lin (2016), Sun (2014), Lai et al. (2016), Lin et al. (2016), Chen and Wang (2017), Huang et al. (2017), Ko et al. (2017), Sezer et al. (2017), Sun and Yeh (2017), Cohen et al. (2018), Meza et al. (2018), Mohamed et al. (2018), Sethi et al. (2018), Lai et al. (2019), Lin and Chen (2019), Dikker et al. (2020), Kim et al. (2020), Kumari and Deb (2020), Ni et al. (2020), Shadiev and Huang (2020), Yang et al. (2020), Aggarwal et al. (2021), Baceviciute et al. (2021), Chen et al. (2021), Grammer et al. (2021), Pajk et al. (2021), Zhang et al. (2021), Bitner and Le (2022), García-Monge et al. (2022), Juan and Chen (2022), Sorochinsky et al. (2022), Sulaiman et al. (2022), Upadhyay et al. (2022), Xu et al. (2022), Xiaojun et al. (2022), Suttidee and Ruanguttamanun (2022), Tang et al. (2023), Zheng et al. (2023)	39
Engagement	Huang et al. (2014), Lee and Chin (2014), Ghali et al. (2016), Ghergulescu and Muntean (2016), Hu and Kuo (2017), Moldovan et al. (2017), Babiker et al. (2019), Eldenfria and Al-Samarraie (2019), Kosmyna and Maes (2019), Zhu et al. (2019), Babiker et al. (2020), Varnavsky and Romanova (2020), Bouhdana et al. (2023)	13
Cognitive load	Mazher et al. (2015), Zhou et al. (2017), Dan and Reiner (2018), Lin and Kao (2018), Khedher et al. (2019), Makransky et al. (2019), Wang et al. (2020)	7
Working memory	Veronica et al. (2022)	1
Synchrony and inter-brain coupling	Dikker et al. (2017), Poulsen et al. (2017), Antonenko et al. (2019), Bevilacqua et al. (2019), Du et al. (2022), Davidesco et al. (2023), Chen et al. (2023)	7
Emotions	Verkijika and De Wet (2015), Robinson et al. (2019), Garces-Gomez et al. (2023)	3
Mindfulness	Martinez and Zhao (2018), Vekety et al. (2022)	2
Learning to create neurofeedback applications	Hernandez-Cuevas et al. (2020)	1
Self-efficacy	Yu et al. (2020)	1
Learning performance	Ramírez-Moreno et al. (2021)	1
Effects of space on EEG activity	Kim and Gero (2023)	1

What purposes are sought?

Studies that seek to assess different cognitive states (attention, engagement, emotions and so on) during the development of educational tasks ($n=29$, 38.15%) are dominant, along with those that seek to compare the impact of different tasks ($n=23$, 30.26%). Reading and writing situations are monitored and compared (e.g., Robinson et al., 2019; Veronica et al., 2022), educational games (Ghali et al., 2016), viewing of different multimedia materials (e.g., Mazher et al., 2015; Poulsen et al., 2017), or exams (Garces-Gomez et al., 2023). In some cases, the procedures are reminiscent of those used in the field of neuromarketing (e.g., Zhu et al., 2019), analysing the effects on engagement or attention of different curricular materials.

Another extended purpose is the use of EEG as a means of neurofeedback ($n=9$, 11.8%) or for the construction of classifiers that allow neurofeedback ($n=9$, 11.8%). In the case of

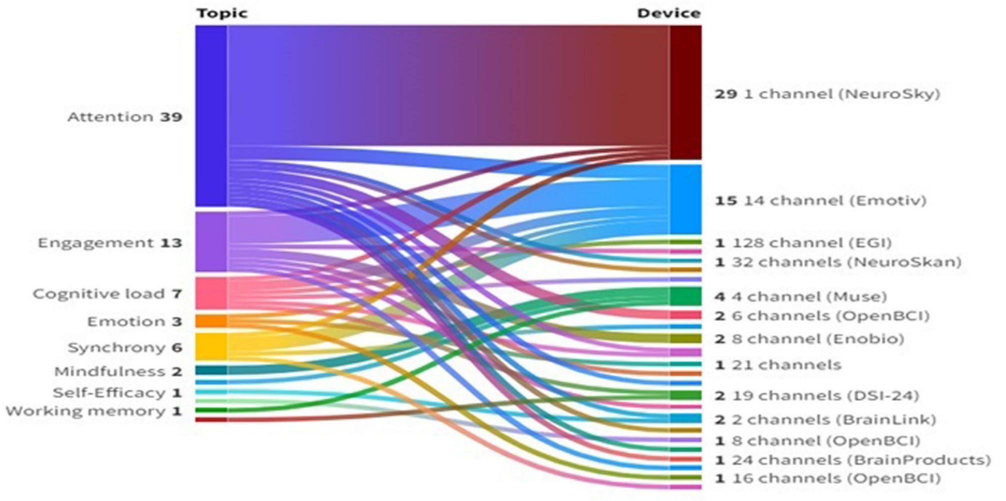

FIGURE 3 Sankey diagram relating the topics studied and the types of devices used.

developing classifiers, the aim is to extract characteristics from the EEG signals recorded in identifiable cognitive situations (in some cases through complementary measures such as self-assessment scales), to subsequently search for a classifier through machine learning procedures, which makes it possible to identify these characteristics in future records, providing feedback through an interface. Linked to this, this review includes an interesting study (Hernandez-Cuevas et al., 2020), focused on the development of neurofeedback applications with EEG devices by secondary education students.

A promising line of work investigates the interaction processes among students (e.g., Antonenko et al., 2019) or between students and teachers (e.g., Bevilacqua et al., 2019; Chen et al., 2023), through hyperscanning procedures, analysing the synchrony between the signals collected from the different participants.

Table 3 shows the studies grouped by purpose.

In what context are the studies carried out?

Semi-naturalistic situations (n=60, 78.9%) predominate over naturalistic ones (n=15, 19.7%). Within both there are different degrees. Among the semi-naturalistic situations, some experiences propose highly controlled situations, with individual interventions, and a strict control of the stimuli (e.g., Mazher et al., 2015). In other cases, an attempt is made to bring students to situations closer to a real experience (e.g., Antonenko et al., 2019). In the case of naturalistic conditions, different degrees of "naturalism" are also apparent, ranging from those cases in which a situation is constructed that tries to reproduce a conventional learning context (e.g., Babiker et al., 2019), to studies that are developed in conventional classrooms (e.g., Chen et al., 2023), even involving the students in the preparation of the devices (e.g., Dikker et al., 2017).

Regarding the degree of naturalism, it should be noted that there are very few studies whose recordings exceed 1h, most of them focusing on recordings obtained in tasks carried out in a short time (between 2 and 10 min). Chen et al.'s (2023) study spans 4 months of regular classroom sessions and demonstrates that the integration of these devices into the classroom is feasible and can provide valuable insights for both teachers and students.

Table 4 shows the studies grouped by their naturalism grade.

TABLE 3 EEG studies analysed grouped by purpose.

Purpose	Studies	Number
Assessment of states during the development of tasks (attention, involvement, working memory, emotions, etc.)	Liu et al. (2013), Sun (2014), Ghali et al. (2016), Ghergulescu and Muntean (2016), Lai et al. (2016), Chen and Wang (2017), Huang et al. (2017), Moldovan et al. (2017), Robinson et al. (2019), Ko et al. (2017), Sezer et al. (2017), Zhou et al. (2017), Cohen et al. (2018), Babiker et al. (2019), Eldenfria and Al-Samarraie (2019), Khedher et al. (2019), Lin and Chen (2019), Makransky et al. (2019), Babiker et al. (2020), Dikker et al. (2020), Kumari and Deb (2020), Varnavsky and Romanova (2020), Pajk et al. (2021), Bitner and Le (2022), Veronica et al. (2022), Garces-Gomez et al. (2023), Suttidee and Ruanguttamanun (2022), Davidesco et al. (2023), Kim and Gero (2023)	29
Comparison of impact of different tasks	Chen and Lin (2016), Mazher et al. (2015), Hu and Kuo (2017), Poulsen et al. (2017), Dan and Reiner (2018), Kosmyna and Maes (2019), Zhu et al. (2019), Kim et al. (2020), Ni et al. (2020), Shadiev and Huang (2020), Wang et al. (2020), Yang et al. (2020), Aggarwal et al. (2021), Grammer et al. (2021), Baceviciute et al. (2021), Chen et al. (2021), García-Monge et al. (2022), Juan and Chen (2022), Upadhyay et al. (2022), Xu et al. (2022), Bouhdana et al. (2023), Tang et al. (2023), Zheng et al. (2023)	23
Neurofeedback	Huang et al. (2014), Lee and Chin (2014), Verkijika and De Wet (2015), Lin et al. (2016), Sun and Yeh (2017), Martinez and Zhao (2018), Sethi et al. (2018), Sorochinsky et al. (2022), Vekety et al. (2022)	9
Creation of a classifier for neurofeedback	Zhou et al. (2017), Lin and Kao (2018), Meza et al. (2018), Mohamed et al. (2018), Lai et al. (2019), Yu et al. (2020), Zhang et al. (2021), Ramírez-Moreno et al. (2021), Sulaiman et al. (2022)	9
Learning to create neurofeedback applications	Hernandez-Cuevas et al. (2020)	1
Analysis of interactions (Hyperscanning)	Dikker et al. (2017), Antonenko et al. (2019), Bevilacqua et al. (2019), Xiaojun et al. (2022), Du et al. (2022), Chen et al. (2023)	6

In these semi-naturalistic or naturalistic situations, ordinary learning tasks ($n=26$, 34.2%) are developed, such as reading, writing or arithmetic, and tasks mediated by different types of technology ($n=49$, 64.47%). Within the latter, some works are oriented to learning in online contexts ($n=11$), and the rest aim to assess the effects of different didactic materials such as educational videos (e.g., Lee & Chin, 2014), learning in virtual environments (e.g., Makransky et al., 2019), learning with augmented reality (Xiaojun et al., 2022), game-based e-learning (Ghergulescu & Muntean, 2016), or the comparison between computer-based and paper-based tasks (Tang et al., 2023).

Table 5 shows the studies grouped by situation.

With what type of participants are these experiences developed?

Work developed with university students dominates (59 studies, 77.6%), decreasing drastically at lower ages. There are few studies developed with elementary school (age: 4–11) and middle school (age: 11–14) populations (Table 6).

Papers with a high number of participants are frequent. We found 41 papers with more than 30 participants (Table 7).

TABLE 4 EEG studies analysed grouped by their naturalism grade.

Naturalism grade	Studies	Number
Semi-naturalistic	Liu et al. (2013), Chen and Lin (2016), Huang et al. (2014), Lee and Chin (2014), Mazher et al. (2015), Verkijika and De Wet (2015), Ghali et al. (2016), Ghergulescu and Muntean (2016), Lai et al. (2016), Lin et al. (2016), Huang et al. (2017), Hu and Kuo (2017), Moldovan et al. (2017), Robinson et al. (2019), Sun and Yeh (2017), Zhou et al. (2017), Cohen et al. (2018), Dan and Reiner (2018), Lin and Kao (2018), Martinez and Zhao (2018), Meza et al. (2018), Mohamed et al. (2018), Sethi et al. (2018), Antonenko et al. (2019), Eldenfria and Al-Samarraie (2019), Khedher et al. (2019), Kosmyna and Maes (2019), Lai et al. (2019), Lin and Chen (2019), Makransky et al. (2019), Zhu et al. (2019), Kim et al. (2020), Kumari and Deb (2020), Ni et al. (2020), Shadiev and Huang (2020), Varnavsky and Romanova (2020), Wang et al. (2020), Yang et al. (2020), Yu et al. (2020), Aggarwal et al. (2021), Baceviciute et al. (2021), Chen et al. (2021), Grammer et al. (2021), Pajk et al. (2021), Zhang et al. (2021), Ramírez-Moreno et al. (2021), Bitner and Le (2022), García-Monge et al. (2022), Juan and Chen (2022), Sorochinsky et al. (2022), Sulaiman et al. (2022), Upadhyay et al. (2022), Vekety et al. (2022), Veronica et al. (2022), Xu et al. (2022), Xiaojun et al. (2022), Garces-Gomez et al. (2023), Suttidee and Ruanguttamanun (2022), Bouhdana et al. (2023), Kim and Gero (2023), Zheng et al. (2023)	60
Naturalistic	Sun (2014), Chen and Wang (2017), Dikker et al. (2017), Ko et al. (2017), Poulsen et al. (2017), Sezer et al. (2017), Bevilacqua et al. (2019), Dikker et al. (2020), Hernandez-Cuevas et al. (2020), Du et al. (2022), Tang et al. (2023), Babiker et al. (2019), Babiker et al. (2020), Davidesco et al. (2023), Chen et al. (2023)	15

In other EEG application areas, studies with more than 40 participants are uncommon. The lengthy protocols for device preparation, data collection and data pre-processing mean that samples are limited. However, many of the studies included in this review use EEG devices with a low number of channels, which facilitates their preparation and signal pre-processing (see Figure 4 on how most of the studies with more than 31 participants are performed with devices with less than 14 channels and rapid preparation). In addition, as will be shown below, several studies do not carry out signal processing, but use the data provided by the algorithms of the devices used.

What types of devices are used?

Most studies are performed with low-cost devices (from \$100 to \$800). Thirty-eight studies (50%) use devices with less than five channels. These devices collect signals through contact sensors (faster to place, but more sensitive to artefacts) with good sampling rates (256–512 Hz). Table 8 shows the studies grouped by number of device channels.

The most widely used devices correspond to the two companies that first started to commercialise consumer EEG headsets (NeuroSky and Emotiv). In both cases, the devices had applications that displayed on an interface values of different states found through proprietary algorithms, based on the collected signal. In the case of NeuroSky and Brainlink (whose hardware is from NeuroSky), the application showed an attention index based in the eSense algorithm. In the case of the Emotiv application, ratings of different states such as engagement, excitement or frustration were displayed.

TABLE 5 EEG studies analysed grouped by situation.

Situation	Studies	Number
Common	Sun (2014), Huang et al. (2014), Dikker et al. (2017), Sun and Yeh (2017), Ko et al. (2017), Sezer et al. (2017), Martinez and Zhao (2018), Bevilacqua et al. (2019), Khedher et al. (2019), Lai et al. (2019), Dikker et al. (2020), Kim et al. (2020), Kumari and Deb (2020), Varnavsky and Romanova (2020), Yang et al. (2020), Yu et al. (2020), García-Monge et al. (2022), Juan and Chen (2022), Sulaiman et al. (2022), Vekety et al. (2022), Veronica et al. (2022), Xu et al. (2022), Bouhdana et al. (2023), Davidesco et al. (2023), Garces-Gomez et al. (2023), Chen et al. (2023)	26
Online	Liu et al. (2013), Lai et al. (2016), Chen and Wang (2017), Robinson et al. (2019), Lin and Kao (2018), Sethi et al. (2018), Eldenfria and Al-Samarraie (2019), Aggarwal et al. (2021), Pajk et al. (2021), Suttidee and Ruanguttamanun (2022), Du et al. (2022)	11
Technology-mediated	Chen and Lin (2016), Lee and Chin (2014), Mazher et al. (2015), Verkijika and De Wet (2015), Ghali et al. (2016), Ghergulescu and Muntean (2016), Lin et al. (2016), Huang et al. (2017), Hu and Kuo (2017), Moldovan et al. (2017), Poulsen et al. (2017), Zhou et al. (2017), Cohen et al. (2018), Dan and Reiner (2018), Meza et al. (2018), Mohamed et al. (2018), Antonenko et al. (2019), Kosmyna and Maes (2019), Lin and Chen (2019), Makransky et al. (2019), Zhu et al. (2019), Hernandez-Cuevas et al. (2020), Ni et al. (2020), Shadiev and Huang (2020), Wang et al. (2020), Baceviciute et al. (2021), Chen et al. (2021), Grammer et al. (2021), Zhang et al. (2021), Ramírez-Moreno et al. (2021), Bitner and Le (2022), Sorochinsky et al. (2022), Upadhyay et al. (2022), Vekety et al. (2022), Xiaojun et al. (2022), Kim and Gero (2023), Tang et al. (2023), Zheng et al. (2023)	38

The indices displayed by the device's own applications have been used in 32 studies (23 using NeuroSky and 4 Emotiv).

In connection with this, we wondered how the data obtained from EEG devices are used?

Mainly, the signals are used in three ways:

- Interpreting indexes provided by the applications of the devices used. In this case, researchers do not access the raw data (32 studies, 42.1%).
- Pre-processing the signals to remove possible artefacts and extracting wave characteristics in the frequency domain, dividing the frequency into canonical frequency bands (delta, theta, alpha, beta and gamma), and then comparing the power spectral densities (PSD). In 24 studies, different analyses are performed in the frequency domain.
- Signal feature extraction to create signal classifiers through different machine learning (13 studies) or deep learning (2 studies) procedures. These classifiers are used to create neurofeedback applications. All these studies build their classifiers from signals collected with devices with less than 15 channels (six of the studies use devices with less than five channels).

Figure 5 shows the evolution over time of the use of these three procedures for processing EEG recordings.

Signal processing is crucial when discussing EEG data in naturalistic or semi-naturalistic settings, given the significant presence of artefacts (noise) that can affect data quality.

Studies based on indexes provided by the devices' applications typically do not apply any form of signal preprocessing, suggesting that these data may be heavily contaminated with movement, electromyographic or vascular artefacts.

In contrast, studies that perform frequency-domain analysis use various preprocessing pipelines. This involves artefact correction, often through visual inspection

TABLE 6 EEG studies analysed grouped by age of the participants.

Participants	Studies	Number
Kindergarten	Lee and Chin (2014)	1
Elementary school–Middle school	Huang et al. (2014), Verkijika and De Wet (2015), Kim et al. (2020), García-Monge et al. (2022), Vekety et al. (2022), Veronica et al. (2022), Xu et al. (2022), Xiaojun et al. (2022)	8
High school	Lai et al. (2016), Chen and Wang (2017), Dikker et al. (2017), Martinez and Zhao (2018), Bevilacqua et al. (2019), Dikker et al. (2020), Hernandez-Cuevas et al. (2020), Chen et al. (2023)	8
University	Liu et al. (2013), Chen and Lin (2016), Sun (2014), Mazher et al. (2015), Ghali et al. (2016), Ghergulescu and Muntean (2016), Lin et al. (2016), Huang et al. (2017), Hu and Kuo (2017), Moldovan et al. (2017), Poulsen et al. (2017), Sezer et al. (2017), Robinson et al. (2019), Sun and Yeh (2017), Ko et al. (2017), Zhou et al. (2017), Cohen et al. (2018), Dan and Reiner (2018), Lin and Kao (2018), Meza et al. (2018), Mohamed et al. (2018), Sethi et al. (2018), Antonenko et al. (2019), Babiker et al. (2019), Eldenfria and Al-Samarraie (2019), Kosmyna and Maes (2019), Khedher et al. (2019), Lai et al. (2019), Lin and Chen (2019), Makransky et al. (2019), Zhu et al. (2019), Babiker et al. (2020), Kumari and Deb (2020), Ni et al. (2020), Shadiev and Huang (2020), Varnavsky and Romanova (2020), Wang et al. (2020), Yang et al. (2020), Yu et al. (2020), Aggarwal et al. (2021), Baceviciute et al. (2021), Chen et al. (2021), Grammer et al. (2021), Pajk et al. (2021), Zhang et al. (2021), Ramírez-Moreno et al. (2021), Bitner and Le (2022), Du et al. (2022), Juan and Chen (2022), Sorochinsky et al. (2022), Sulaiman et al. (2022), Upadhyay et al. (2022), Garces-Gomez et al. (2023), Suttidee and Ruanguttamanun (2022), Bouhdana et al. (2023), Davidesco et al. (2023), Kim and Gero (2023), Tang et al. (2023), Zheng et al. (2023)	59

(rejecting contaminated segments) or automated methods such as the Artefact Subspace Reconstruction Method or Independent Component Analysis (ICA, a statistical method for decomposing multivariate data into its statistically independent hidden components). Most studies use toolboxes like EEGLab or Fieldtrip in Matlab, often with custom code, and to a lesser extent, BrainStorm, BrainVision Analyser, and different Matlab or Python-based tools. Only eight studies explicitly mention the number of channels or segments discarded, or the proportion of data that was corrected.

Among the studies that use machine learning (ML) or deep learning (DL) techniques to develop signal classifiers, six works use raw unprocessed data, while the rest follow pre-processing procedures similar to those described in frequency-domain analysis.

DISCUSSION

This review shows the potential use of EEG devices in educational contexts to monitor in real time the effects of different educational tasks and materials (reading, writing, calculation, listening to lectures or educational videos, participation in educational games in different multimedia environments and so on) and, in some cases, to provide immediate feedback to students and teachers. However, despite the low cost of some of the devices on the market (from $100), their use is still very restricted, limited to experimental environments with university students (77.6% of the studies).

Of the studies analysed, 68.4% focus on the analysis or improvement of attention or engagement. Undoubtedly, these aspects are crucial in any learning process. However, it

TABLE 7 EEG studies analysed grouped by number of participants.

Number of participants	Studies	Number
1–10	Mazher et al. (2015), Hu and Kuo (2017), Martinez and Zhao (2018), Varnavsky and Romanova (2020), García-Monge et al. (2022), Sulaiman et al. (2022), Garces-Gomez et al. (2023)	7
11–20	Chen and Lin (2016), Huang et al. (2014), Dikker et al. (2017), Dan and Reiner (2018), Robinson et al. (2019), Ko et al. (2017), Bevilacqua et al. (2019), Khedher et al. (2019), Zhu et al. (2019), Hernandez-Cuevas et al. (2020), Aggarwal et al. (2021), Chen et al. (2021), Pajk et al. (2021), Ramírez-Moreno et al. (2021), Sorochinsky et al. (2022), Upadhyay et al. (2022), Kim and Gero (2023)	17
21–30	Liu et al. (2013), Sezer et al. (2017), Babiker et al. (2020), Dikker et al. (2020), Kim et al. (2020), Ni et al. (2020), Grammer et al. (2021), Bitner and Le (2022), Veronica et al. (2022)	9
More than 30	Sun (2014), Lee and Chin (2014), Verkijika and De Wet (2015), Ghali et al. (2016), Ghergulescu and Muntean (2016), Lai et al. (2016), Lin et al. (2016), Chen and Wang (2017), Huang et al. (2017), Moldovan et al. (2017), Poulsen et al. (2017), Sun and Yeh (2017), Cohen et al. (2018), Lin and Kao (2018), Mohamed et al. (2018), Sethi et al. (2018), Antonenko et al. (2019), Babiker et al. (2019), Eldenfria and Al-Samarraie (2019), Kosmyna and Maes (2019), Lai et al. (2019), Lin and Chen (2019), Makransky et al. (2019), Kumari and Deb (2020), Shadiev and Huang (2020), Wang et al. (2020), Yang et al. (2020), Yu et al. (2020), Baceviciute et al. (2021), Zhang et al. (2021), Du et al. (2022), Juan and Chen (2022), Vekety et al. (2022), Xu et al. (2022), Xiaojun et al. (2022), Suttidee and Ruanguttamanun (2022), Bouhdana et al. (2023), Davidesco et al. (2023), Tang et al. (2023), Zheng et al. (2023), Chen et al. (2023)	41

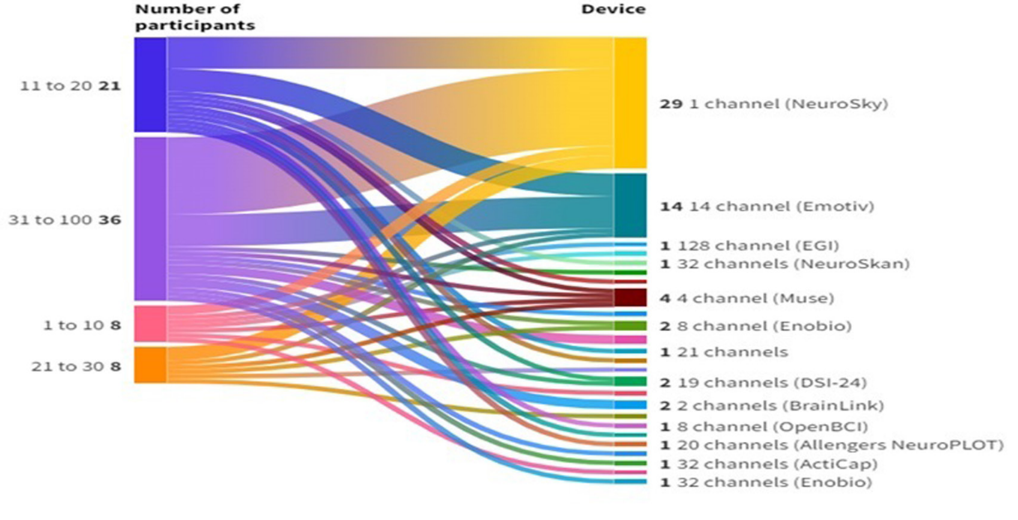

FIGURE 4 Sankey diagram relating the number of participants and the types of devices used.

is worth questioning the extent to which this research direction may be influenced by the characteristics of the devices used and the applications offered by commercial companies (51.92% of the studies on attention and engagement utilise the indexes provided by the applications used). There may be an interesting relationship occurring that limits the range

TABLE 8 EEG studies analysed grouped by number of device channels.

Channels	Studies	Number
1–5	Liu et al. (2013), Chen and Lin (2016), Sun (2014), Verkijika and De Wet (2015), Lai et al. (2016), Lin et al. (2016), Chen and Wang (2017), Huang et al. (2017), Hu and Kuo (2017), Sezer et al. (2017), Sun and Yeh (2017), Lin and Kao (2018), Martinez and Zhao (2018), Sethi et al. (2018), Kosmyna and Maes (2019), Kim et al. (2020), Lai et al. (2019), Lin and Chen (2019), Kumari and Deb (2020), Ni et al. (2020), Shadiev and Huang (2020), Yang et al. (2020), Yu et al. (2020), Aggarwal et al. (2021), Chen et al. (2021), Pajk et al. (2021), Zhang et al. (2021), Bitner and Le (2022), Du et al. (2022), Juan and Chen (2022), Sulaiman et al. (2022), Vekety et al. (2022), Veronica et al. (2022), Xiaojun et al. (2022), Suttidee and Ruanguttamanun (2022), Tang et al. (2023), Zheng et al. (2023), Chen et al. (2023)	38
6–15	Huang et al. (2014), Lee and Chin (2014), Verkijika and De Wet (2015), Ghali et al. (2016), Ghergulescu and Muntean (2016), Dikker et al. (2017), Moldovan et al. (2017), Zhou et al. (2017), Mohamed et al. (2018), Babiker et al. (2019), Bevilacqua et al. (2019), Eldenfria and Al-Samarraie (2019), Khedher et al. (2019), Makransky et al. (2019), Babiker et al. (2020), Dikker et al. (2020), Baceviciute et al. (2021), Ramírez-Moreno et al. (2021), García-Monge et al. (2022), Sorochinsky et al. (2022)	20
16–25	Dan and Reiner (2018), Robinson et al. (2019), Wang et al. (2020), Grammer et al. (2021), Upadhyay et al. (2022), Xu et al. (2022), Kim and Gero (2023)	7
26–35	Ko et al. (2017), Varnavsky and Romanova (2020), Bouhdana et al. (2023), Davidesco et al. (2023)	4
+ de 36	Mazher et al. (2015), Cohen et al. (2018), Zhu et al. (2019)	3

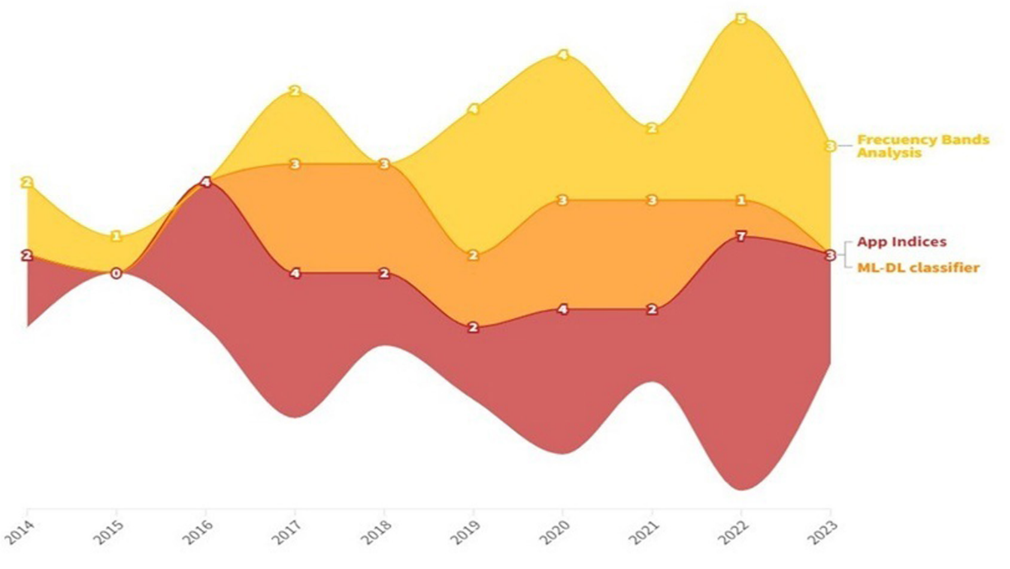

FIGURE 5 Evolution over time of the use of different procedures for processing EEG recordings.

of study topics: certain companies marketing low-cost EEG devices tailor their applications towards neuromarketing, driving, video games or learning situations. Consequently, many researchers access these devices (due to their affordability and ease of use) and base their data on the indices provided by these applications.

In any case, it is a promising step forward to have devices that make it possible to improve students' metacognition, providing them with real-time information about their states through neurofeedback, and that provide teachers with information about the effect of their materials and proposals in order to better adjust them to personal needs and processes.

Mainly, the studies aim to analyse the effects of different educational activities and materials on students (on attention, engagement, workload, or synchronicity among students and between students and teachers), and to build and test classifiers that allow real-time neurofeedback. Nevertheless, perhaps the development of knowledge and applications in this field are still incipient, since we have not found studies that show the development of educational experiences in which these methods are applied for a sustained period of time (with the exception of Chen et al.'s 2023 study, which extends over 4 months of classroom sessions). There is no follow-up of the contributions made (for example, in the use of brain computer interface [BCI] and neurofeedback), studying their prolonged application in educational contexts through more intensive methods such as case studies, design-based research or action-research.

In order to conduct this type of research, it is crucial to implement projects that take into account the interests of teachers, students, families and researchers and foster interdisciplinary collaboration (Katzir & Paré-Blagoev, 2006). Moreover, researchers need to refine their research questions to gain a better understanding of the realities within the educational settings (Liu & Zhang, 2021) and effectively communicate the potential of brain research to the educational community (Mason, 2009). To accomplish this, it is essential to pursue partnership models that consider the needs and demands of teachers, students and families (Howard-Jones et al., 2016; Liu & Zhang, 2021) and ensure that these collaborative experiences are meaningfully integrated into educational programmes. Furthermore, the establishment of these partnerships relies on cultivating relationships based on mutual trust, which can only be developed over time (Liu & Zhang, 2021).

The need to deploy a 'real-world neuroscience' (Matusz et al., 2019; Shamay-Tsoory & Mendelsohn, 2019) seems to present some limitations when developing studies in educational contexts (García-Monge et al., 2023; Janssen et al., 2021). As noted, most of the studies analysed are conducted in semi-naturalistic conditions with population close to the research teams (university students) and with low-end devices.

The cost of the devices (Patil et al., 2022; Varma et al., 2008) and the complexity of their integration in classrooms (García-Monge et al., 2023; Janssen et al., 2021), may be behind their low use in naturalistic conditions, in groups of schoolchildren and for prolonged periods of time. Integrating these devices in naturalistic contexts involves high economic and organisational costs (obtaining permissions, agreement with teachers on the purpose and plan of action, preparation of the devices, verification of contact and signal quality, equipment to receive the signals from each device, avoiding interference from the signals sent by each device to each receiving equipment, etc.). All of this may be getting simpler with the emergence of simple devices geared for simultaneous use (Lee et al., 2019) and the improvement of signal quality collected by fast setup devices with dry sensors. In general, dry electrodes reduce device placement times, but their signal may be more affected by artefacts (Mathewson et al., 2017; Shad et al., 2020). The ease of placement, as well as not relying on a substance that loses conductive properties if recording is prolonged, makes these sensors very attractive for use in real-world contexts with broad applications not only in the field of research, but in device management through electroencephalographic signals (BCI); thus, there are constant advances in this field (e.g., Hajare & Kadam, 2021; Kim et al., 2022; Li et al., 2020). These future advances may correct the limitations in the low signal quality of some of the most commonly used devices in the presented studies (Duvinage et al., 2013; Li et al., 2020; Maskeliunas et al., 2016). Moreover, some EEG devices with built-in automatic artefact removal filters (e.g., artefact subspace reconstruction algorithm [ASR], used by mBrainTrain's SmartingPro device, or g-Tec's Online Signal Conditioning & Artefact Removal) are now starting to be commercialised. A review on the subject can be found in Seok et al. (2021). In any case, the collected signal must be pre-processed, for which interesting tools are beginning to appear, such as those offered on the Medusa platform (Santamaría-Vázquez et al., 2023) oriented to the development of BCI systems.

Beyond technical or organisational limitations, Xu et al. (2022) point out that EEG studies with children in naturalistic settings often have limitations in isolating specific neurocognitive processes, as well as being more susceptible to artefact contamination. It is a challenge to integrate good EEG research designs into the everyday classroom, but the review provides good examples of how this can be achieved by involving students (e.g., Dikker et al., 2017), which can result in learning about brain activity, neurofeedback processes and metacognition (e.g., Bevilacqua et al., 2019; Dikker et al., 2020; Xu et al., 2022). In addition, as Han et al. (2019) point out, methodological heuristics acquired in naturalistic and semi-naturalistic research in the field of video games could endow the field of neuroimaging in educational contexts with an interesting body of knowledge.

Another aspect to be analysed is the interpretation of the signals. We have seen that 42.1% of the studies analysed base their metrics on the indexes provided by the applications of the EEG devices used. It should be considered that these indices are based on data collected in specific situations and populations. By varying the ages and characteristics of the participants or the context of application, the markers may lose validity. Authors such as Larsen et al. (2021) question, for example, whether attention metrics with EEG devices are reliable and whether attention is a measurable phenomenon that can be reasonably represented by a metric. Attention encompasses various cognitive processes (e.g., Petersen & Posner, 2012) that can hardly be reduced to data obtained from one or two electrodes. At best, we would be referring to a part of the attentional process. In addition to this, we must consider the interpersonal variability in mental processes and EEG recordings (e.g., Basile et al., 2007) or variations due to developmental maturation (e.g., Ramos-Loyo et al., 2022). Ienca et al. (2018) highlight another limitation of these measurements provided by applications from companies that commercialise low-cost EEG devices: their limited traceability and verifiability, given their 'black box algorithms'. Therefore, caution must be exercised when considering the emergence of commercial neurofeedback solutions that are generalised to groups of students, as they may influence educational decisions based on unreliable data and inadequately tailored to each individual student.

In principle, the extensive literature on neural correlates associated with different cognitive functions and the utilisation of ML or DL procedures allow for the reduction of sensor numbers and limited placement areas to record specific cognitive processes. However, there is a risk in extrapolating neuromarkers extracted from highly controlled laboratory conditions to define processes occurring in more complex situations. The limited number of electrodes in some devices poses challenges for accurate source modelling (e.g., Akalin Acar & Makeig, 2013) and restricts the range of processes that can be studied and the possible analyses (e.g., Lau-Zhu et al., 2019). In a more cautious approach, recordings should encompass broader areas of the scalp (using more than 15 channels). This would allow:

- Better pre-processing, being able to dispense with channels with too many artefacts (something common in the work with children or in naturalistic situations).
- Better reconstruction of sources to determine areas of interest.
- Studies of connectivity between areas.
- Extraction of more characteristics from the signals that would allow better adjustment of the classifiers associated with different cognitive processes.

The development of AI models could help streamline these procedures by using raw data from a few channels to differentiate between various cognitive states. This use of AI could reduce computational demands for real-time analysis of signals from a group of students and display measures of interest, such as inter-brain coupling (Chen et al., 2023).

In line with the work of Jiang et al. (2024), which focuses on the use of brain-computer interfaces in education, the results report that, as with any new technology, the adoption rate in educational contexts is slow. The economic and training costs are obvious barriers to incorporating any new device into educational practice. Considering the Gartner Hype Cycle (e.g., Dedehayir & Steinert, 2016), it could be said that the application of these devices in educational settings, after the initial phases of 'Technology Trigger' and the 'Peak of Inflated Expectations', appears to be entering the 'Trough of Disillusionment'. It is probable that the accumulation of knowledge, advancements in artificial intelligence (AI), and the improvement and cost reduction of sensors may soon propel these technologies into the 'Slope of Enlightenment', where second-generation products will emerge, offering decreased costs and increased reliability and usability in real-world contexts.

A final crucial aspect for discussion pertains to the ethical implications of employing this technology within the educational setting, involving the extraction of physiological signals from students and accessing their 'black box' of privacy. The integration of neurotechnology in classrooms holds significant value in advancing our comprehension of the underlying processes involved in proposed tasks, thereby facilitating educational environments that can be better tailored to the individual needs and characteristics of students. However, as elucidated by Janssen et al. (2021), drawing on the work of Rose and Abi-Rached (2014), a cautionary note must be raised regarding the potential for treating the brain as a 'biopolitical resource', thereby promoting processes of optimisation and competitiveness. Scholars like Williamson (2018) further caution against the perils of 'neurogovernance', which aims to scrutinise the brain to shape specific abilities, and, as Ienca et al. (2022) observe, the risk that AI features may override the intentionality, volition and agency of the user. Given the well-acknowledged political dimension of education, it is essential to conscientiously consider the objectives and implications of such studies.

In summary, the results of this review show us an incipient field with great potential for research and improvement in educational practice. Currently, the cost of the devices and the necessary human and organisational resources limit the extension of these experiences to completely naturalistic situations. Moreover, the predominance of studies focused on university students and the use of low-cost EEG devices with fewer channels restricts the generalisability and accuracy of the findings. Future research should prioritise the inclusion of more diverse educational settings, the use of advanced EEG technology, and longitudinal designs that can better integrate these tools into everyday classroom practices.

However, work in this direction will generate a corpus of knowledge that will facilitate future applications. This, together with the improvement of the sensors and possibly the lower cost of the devices, will allow their extension for the benefit of education. Additionally, these technologies hold the potential to provide real-time feedback on cognitive states such as attention and engagement, enabling more personalised and adaptive teaching strategies. Nonetheless, the use of these devices in educational contexts raises ethical concerns, particularly the influence on teaching decisions by opaque commercial algorithms that may oversimplify assessments of specific cognitive processes and fail to adapt to individual student characteristics.

AUTHOR CONTRIBUTIONS

Alfonso García-Monge: Conceptualization; data curation; formal analysis; writing – original draft. **Henar Rodríguez-Navarro:** Conceptualization; data curation; formal analysis; writing – original draft. **Daniel Bores-García:** Methodology; writing – review and editing; writing – original draft; conceptualization. **Gustavo González-Calvo:** Conceptualization; writing – original draft; writing – review and editing; methodology.

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest that could have influenced the conduct, outcomes, or reporting of this study. No financial, professional, or personal relationships exist that could be perceived as inappropriately affecting the research.

DATA AVAILABILITY STATEMENT

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

ETHICS STATEMENT

This research has been conducted in full compliance with the ethical guidelines applicable to the field of study.

ORCID

Alfonso García-Monge https://orcid.org/0000-0002-4535-5628
Henar Rodríguez-Navarro https://orcid.org/0000-0001-6993-8441
Daniel Bores-García https://orcid.org/0000-0003-2522-8493
Gustavo González-Calvo https://orcid.org/0000-0002-4637-0168

REFERENCES

Aggarwal, S., Lamba, M., Verma, K., Khuttan, S., & Gautam, H. (2021). A preliminary investigation for assessing attention levels for massive online open courses learning environment using eeg signals: An experimental study. *Human Behavior and Emerging Technologies*, *3*(5), 933–941. https://doi.org/10.1002/hbe2.274

Akalin Acar, Z., & Makeig, S. (2013). Effects of forward model errors on EEG source localization. *Brain Topography*, *26*(3), 378–396. https://doi.org/10.1007/s10548-012-0274-6

Al-Nafjan, A., & Aldayel, M. (2022). Predict students' attention in online learning using EEG data. *Sustainability*, *14*(11), 6553. https://doi.org/10.3390/su14116553

Anderson, J. R., Reder, L. M., & Simon, H. A. (1996). Situated learning and education. *Educational Researcher*, *25*(4), 5–11. https://doi.org/10.3102/0013189X025004005

Antonenko, P. D., Davis, R., Wang, J., & Celepkolu, M. (2019). On the same wavelength: Exploring team neurosynchrony in undergraduate dyads solving a cyberlearning problem with collaborative scripts. *Mind, Brain, and Education*, *13*(1), 4–13. https://doi.org/10.1111/mbe.12187

Apicella, A., Arpaia, P., Frosolone, M., Improta, G., Moccaldi, N., & Pollastro, A. (2022). EEG-based measurement system for monitoring student engagement in learning 4.0. *Scientific Reports*, *12*(1), 5857.

Babiker, A., Fayeb, I., & Malikc, A. S. (2020). Neural network for detection of Students' interest using approximate entropy features of EEG data. *Asia Pacific Journal of Neurotherapy (APJNT)*, *2*(1), 022–026. https://apjnt.org/wp-content/uploads/2021/03/Areej-Babiker_Ibrahim-Faye_Aamir-Saeed-Malik_Neural-Network-for-Detection-of-Student-interest-using-Approximate-Entropy-Featyre-of-EEG-data_APJNT_Journal_Vol2_No1_2020.pdf

Babiker, A., Fayeb, I., Mumtaz, W., Malik, A. S., & Sato, H. (2019). EEG in classroom: EMD features to detect situational interest of students during learning. *Multimedia Tools and Applications*, *78*, 16261–16281. https://doi.org/10.1007/s11042-018-7016-z

Baceviciute, S., Terkildsen, T., & Makransky, G. (2021). Remediating learning from non-immersive to immersive media: Using EEG to investigate the effects of environmental embeddedness on reading in virtual reality. *Computers and Education*, *164*, 104122. https://doi.org/10.1016/j.compedu.2020.104122

Basile, L. F., Anghinah, R., Ribeiro, P., Ramos, R. T., Piedade, R., Ballester, G., & Brunetti, E. P. (2007). Interindividual variability in EEG correlates of attention and limits of functional mapping. *International Journal of Psychophysiology*, *65*(3), 238–251. https://doi.org/10.1016/j.ijpsycho.2007.05.001

Bazzani, A., Ravaioli, S., Trieste, L., Faraguna, U., & Turchetti, G. (2020). Is EEG suitable for marketing research? A systematic review. *Frontiers in Neuroscience*, *14*, 594566. https://doi.org/10.3389/fnins.2020.594566

Bevilacqua, D., Davidesco, I., Wan, L., Chaloner, K., Rowland, J., Ding, M., Poeppel, D., & Dikker, S. (2019). Brain-to-brain synchrony and learning outcomes vary by student–teacher dynamics: Evidence from a real-world classroom electroencephalography study. *Journal of Cognitive Neuroscience*, *31*(3), 401–411. https://doi.org/10.1162/jocn_a_01274

Bitner, R. A., & Le, N. T. (2022). Can EEG-devices differentiate attention values between incorrect and correct solutions for problem-solving tasks? *Journal of Information and Telecommunication*, *6*(2), 121–140. https://doi.org/10.1080/24751839.2021.1950319

Bouhdana, I., Charland, P., Foisy, L. B., Lapierre, H. G., Léger, P. M., Allaire-Duquette, G., Potvin, P., Masson, S., Riopel, M., & Mahhou, M. A. (2023). Effects of reading contextualized physics problems among men and women: A psychophysiological approach. *Trends in Neuroscience and Education*, *30*, 100199. https://doi.org/10.1016/j.tine.2023.100199

Brown, J. S., Collins, A., & y Duguid, P. (1989). Situated cognition and the culture of learning. *Educational Researcher*, *18*(1), 32–42. https://doi.org/10.3102/0013189X018001032

Chavez, M., Grosselin, F., Bussalb, A., Fallani, F. D. V., & Navarro-Sune, X. (2018). Surrogate-based artifact removal from single-channel EEG. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *26*(3), 540–550. https://doi.org/10.1109/TNSRE.2018.2794184

Chen, C., & Wang, J. (2017). Effects of online synchronous instruction with an attention monitoring and alarm mechanism on sustained attention and learning performance. *Interactive Learning Environments*, *26*, 427–443. https://doi.org/10.1080/10494820.2017.1341938

Chen, C. M., & Lin, Y. J. (2016). Effects of different text display types on reading comprehension, sustained attention and cognitive load in mobile reading contexts. *Interactive Learning Environments*, *24*(3), 553–571. https://doi.org/10.1080/10494820.2014.891526

Chen, J., Qian, P., Gao, X., Li, B., Zhang, Y., & Zhang, D. (2023). Inter-brain coupling reflects disciplinary differences in real-world classroom learning. *Npj Science of Learning*, *8*(1), 11. https://doi.org/10.1038/s41539-023-00162-1

Chen, Y., Wang, Y., Zhou, J., Gao, J., Gao, G., & Zhang, W. (2021, December). Study on the influence of interaction style on learners. In *2021 IEEE International Conference on Engineering, Technology and Education (TALE)* (pp. 298–303). IEEE. https://doi-org.ponton.uva.es/10.1109/TALE52509.2021.9678521

Choi, Y., Kim, M., & Chun, C. (2019). Effect of temperature on attention ability based on electroencephalogram measurements. *Building and Environment*, *147*, 299–304. https://doi.org/10.1016/j.buildenv.2018.10.020

Cohen, S. S., Madsen, J., Touchan, G., Robles, D., Lima, S. F. A., Henin, S., & Parra, L. C. (2018). Neural engagement with online educational videos predicts learning performance for individual students. *Neurobiology of Learning and Memory*, *155*, 60–64. https://doi.org/10.1016/j.nlm.2018.06.011

Daly, I., Bourgaize, J., & Vernitski, A. (2019). Mathematical mindsets increase student motivation: Evidence from the EEG. *Trends in Neuroscience and Education*, *15*, 18–28. https://doi.org/10.1016/j.tine.2019.02.005

Dan, A., & Reiner, M. (2018). Reduced mental load in learning a motor visual task with virtual 3D method. *Journal of Computer Assisted Learning*, *34*(1), 84–93. https://doi.org/10.1111/jcal.12216

Davidesco, I. (2020). Brain-to-brain synchrony in the STEM classroom. *CBE Life Sciences Education*, *19*(3), es8. https://doi.org/10.1187/cbe.19-11-0258

Davidesco, I., Laurent, E., Valk, H., West, T., Milne, C., Poeppel, D., & Dikker, S. (2023). The temporal dynamics of brain-to-brain synchrony between students and teachers predict learning outcomes. *Psychological Science*, *34*(5), 633–643. https://doi.org/10.1177/09567976231163872

Dedehayir, O., & Steinert, M. (2016). The hype cycle model: A review and future directions. *Technological Forecasting and Social Change*, *108*, 28–41. https://doi.org/10.1016/j.techfore.2016.04.005

Dikker, S., Haegens, S., Bevilacqua, D., Davidesco, I., Wan, L., Kaggen, L., McClintock, J., Chaloner, K., Ding, M., West, T., & Poeppel, D. (2020). Morning brain: Real-world neural evidence that high school class times matter. *Social Cognitive and Affective Neuroscience*, *15*(11), 1193–1202. https://doi.org/10.1093/scan/nsaa142

Dikker, S., Wan, L., Davidesco, I., Kaggen, L., Oostrik, M., McClintock, J., Rowland, J., Michalareas, G., van Bavel, J. J., Ding, M., & Poeppel, D. (2017). Brain-to-brain synchrony tracks real-world dynamic group interactions in the classroom. *Current Biology*, *27*(9), 1375–1380. https://doi.org/10.1016/j.cub.2017.04.002

Du, X., Zhang, L., Hung, J. L., Li, H., Tang, H., & Xie, Y. (2022). Understand group interaction and cognitive state in online collaborative problem solving: Leveraging brain-to-brain synchrony data. *International Journal of Educational Technology in Higher Education*, *19*(1), 52. https://doi.org/10.1186/s41239-022-00356-4

Duvinage, M., Castermans, T., Petieau, M., Hoellinger, T., Cheron, G., & Dutoit, T. (2013). Performance of the Emotiv Epoc headset for P300-based applications. *Biomedical Engineering Online*, *12*, 56. https://doi.org/10.1186/1475-925X-12-56

Eldenfria, A., & Al-Samarraie, H. (2019). Towards an online continuous adaptation mechanism (OCAM) for enhanced engagement: An EEG study. *International Journal of Human–Computer Interaction*, *35*(20), 1960–1974. https://doi.org/10.1080/10447318.2019.1595303

Farahany, N. A. (2023). *The Battle for your brain: Defending the right to think freely in the age of Neurotechnology*. St Martin's Press.

Fischer, K. W., Bernstein, J. H., & Immordino-Yang, M. H. (Eds.). (2007). *Mind, brain, and education in reading disorders* (Vol. *11*). Cambridge University Press.

Garces-Gomez, Y., Lara-Escobar, R., López-Jimenez, P. A., Toro-García, N., Cardenas-Jimenez, J. I., Gonzalez-Correa, C., & Gonzalez-Correa, C. (2023). Exploring students' emotional state during a test-related task using wearable electroencephalogram. *International Journal of Electrical and Computer Engineering*, *13*(1), 307–314. https://doi.org/10.11591/ijece.v13i1.pp307-314

García-Monge, A., Rodríguez-Navarro, H., Bores-García, D., & González-Calvo, G. (2022). Comparison of children's inhibitory control, attention and working memory in three different throwing games. *Retos*, *45*, 502–513. https://doi.org/10.47197/retos.v45i0.92478

García-Monge, A., Rodríguez-Navarro, H., & Marbán-Prieto, J. M. (2023). Potentialities and limitations of the use of EEG devices in educational contexts. *Comunicar*, *76*(3), 47–57. https://doi.org/10.3916/C76-2023-04

Ghali, R., Ouellet, S., & Frasson, C. (2016). LewiSpace: An exploratory study with a machine learning model in an educational game. *Journal of Education and Training Studies*, *4*(1), 192–201.

Ghergulescu, I., & Muntean, C. H. (2016). ToTCompute: un novedoso mecanismo de cálculo de umbral de TimeOnTask basado en EEG para el modelado y la supervisión de la participación. *Revista Internacional de Inteligencia Artificial en Educación*, *26*, 821–854. https://doi.org/10.1007/s40593-016-0111-2

Grammer, J. K., Xu, K., & Lenartowicz, A. (2021). Effects of context on the neural correlates of attention in a college classroom. *Npj Science of Learning*, *6*(1), 15. https://doi.org/10.1038/s41539-021-00094-8

Hajare, R., & Kadam, S. (2021). Comparative study analysis of practical EEG sensors in medical diagnoses. *Global Transitions Proceedings*, *2*(2), 467–475. https://doi.org/10.1016/j.gltp.2021.08.009

Hall, L., & Johansson, P. (2003). Neurofeedback and Metacognition. *Proc. AIED 2003, Supplementary Proceedings: Metacognition and Self-regulation in Learning with Metacognitive Tools* (pp. 541–556). https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=2357f017b400ad48b09171fcbaf0ebee6454fd1f

Han, H., Soylu, F., & Anchan, D. M. (2019). Connecting levels of analysis in educational neuroscience: A review of multi-level structure of educational neuroscience with concrete examples. *Trends in Neuroscience and Education*, *17*, 100113. https://doi.org/10.1016/j.tine.2019.100113

Hernandez-Cuevas, B., Egbert, W., Denham, A., Mehul, A., & Crawford, C. S. (2020, April). Changing minds: Exploring brain-computer interface experiences with high school students. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1–10). https://doi.org/10.1145/3334480.3382981

Howard-Jones, P. A., Varma, S., Ansari, D., Butterworth, B., De Smedt, B., Goswami, U., Laurillard, D., & Thomas, M. S. C. (2016). The principles and practices of educational neuroscience: Comment on bowers (2016). *Psychological Review*, *123*(5), 620–627. https://doi.org/10.1037/rev0000036

Hu, P. C., & Kuo, P. C. (2017, October). Adaptive learning system for E-learning based on EEG brain signals. In *2017 IEEE 6th Global Conference on Consumer Electronics (GCCE)* (pp. 1–2). IEEE. https://doi.org/10.1109/GCCE.2017.8229382

Huang, J., Yu, C., Wang, Y., Zhao, Y., Liu, S., Mo, C., Liu, J., Zhang, L., & Shi, Y. (2014). FOCUS: Enhancing children's engagement in reading by using contextual BCI training sessions. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 1905–1908). https://doi.org/10.1145/2556288.2557339

Huang, Y. M., Liu, M. C., Lai, C. H., & Liu, C. J. (2017). Using humorous images to lighten the learning experience through questioning in class. *British Journal of Educational Technology*, *48*(3), 878–896. https://doi.org/10.1111/bjet.12459

Ienca, M., Fins, J. J., Jox, R. J., Jotterand, F., Voeneky, S., Andorno, R., Ball, T., Castelluccia, C., Chavarriaga, R., Chneiweiss, H., Ferretti, A., Friedrich, O., Hurst, S., Merkel, G., Molnár-Gábor, F., Rickli, J.-M., Scheibner, J., Vayena, E., Yuste, R., & Kellmeyer, P. (2022). Towards a governance framework for brain data. *Neuroethics*, *15*(2), 20. https://doi.org/10.1007/s12152-022-09498-8

Ienca, M., Haselager, P., & Emanuel, E. J. (2018). Brain leaks and consumer neurotechnology. *Nature Biotechnology*, *36*(9), 805–810. https://doi.org/10.1038/nbt.4240

Jalali, S., & Wohlin, C. (2012, September). Systematic literature studies: Database searches vs. backward snowballing. In *Proceedings of the ACM-IEEE International Symposium on Empirical Software Engineering and Measurement* (pp. 29–38) https://dl.acm.org/doi/pdf/10.1145/2372251.2372257?casa_token=YhlRG5Pm-6hcAAAAA:k0pIvX04Z1jQHPmRJlGo10tdS2aVQdIBDEumJcveWTKL0dpEZXpnn0i24MwkjyqBqCdKi4os-UeDH

Janssen, T. W. P., Grammer, J. K., Bleichner, M. G., Bulgarelli, C., Davidesco, I., Dikker, S., Jasińska, K. K., Siugzdaite, R., Vassena, E., Vatakis, A., Zion-Golumbic, E., & van Atteveldt, N. (2021). Opportunities and limitations of Mobile neuroimaging Technologies in Educational Neuroscience. *Mind, Brain and Education*, *15*(4), 354–370. https://doi.org/10.1111/mbe.12302

Jiang, Y., Huang, Q., & Li, Y. (2024). Application strategies of brain-computer interface in education from the perspective of innovation diffusion theory. *Brain-Apparatus Communication: A Journal of Bacomics*, *3*(1), 2376368. https://doi.org/10.1080/27706710.2024.2376368

Juan, Y.-K., & Chen, Y. (2022). The influence of indoor environmental factors on learning: An experiment combining physiological and psychological measurements. *Building and Environment*, *221*, 109299. https://doi.org/10.1016/j.buildenv.2022.109299

Jung, T. P., Makeig, S., Westerfield, M., Townsend, J., Courchesne, E., & Sejnowski, T. J. (2000). Removal of eye activity artifacts from visual event-related potentials in normal and clinical subjects. *Clinical Neurophysiology*, *111*(10), 1745–1758. https://doi.org/10.1016/S1388-2457(00)00386-2

Katzir, T., & Paré-Blagoev, J. (2006). Applying cognitive neuroscience research to education: The case of literacy. *Educational Psychologist*, *41*, 53–74. https://doi.org/10.1207/s15326985ep4101_6

Kavitha, S., Raghuraman, G., Kavithasri, A., Aishvarya, S., & Janani, B. (2023). Learning behaviour analysis of online course learners using EEG and facial expression data. *Measurement: Sensors*, *25*, 100669. https://doi.org/10.1016/j.measen.2023.100669

Khedher, A. B., Jraidi, I., & Frasson, C. (2019). Tracking students' mental engagement using EEG signals during an interaction with a virtual learning environment. *Journal of Intelligent Learning Systems and Applications*, *11*(1), 1–14. https://doi.org/10.4236/jilsa.2019.111001

Kim, H., Kim, E., Choi, C., & Yeo, W. H. (2022). Advances in soft and dry electrodes for wearable health monitoring devices. *Micromachines*, *13*(4), 629. https://doi.org/10.3390/mi13040629

Kim, N., & Gero, J. S. (2023). Neurophysiological responses to Biophilic design: A pilot experiment using VR and EEG. In *Design computing and Cognition'22* (pp. 235–253). Springer International Publishing. https://doi.org/10.1007/978-3-031-20418-0_15

Kim, S.-O., Oh, Y.-A., & Park, S.-A. (2020). Foliage plants improve concentration and emotional condition of elementary school students performing an intensive assignment. *HortScience*, *55*(3), 378–385. https://doi.org/10.21273/HORTSCI14757-19

Ko, L. W., Komarov, O., Hairston, W. D., Jung, T. P., & Lin, C. T. (2017). Sustained attention in real classroom settings: An EEG study. *Frontiers in Human Neuroscience*, *11*, 388. https://doi.org/10.3389/fnhum.2017.00388

Kosmyna, N., & Maes, P. (2019). AttentivU: An EEG-based closed-loop biofeedback system for real-time monitoring and improvement of engagement for personalized learning. *Sensors*, *19*(23), 5200. https://doi.org/10.3390/s19235200

Kumari, P., & Deb, S. (2020, July). EEG cross validation of effective mobile technology by analyzing attention level in classroom. In *2020 International Conference on Electronics and Sustainable Communication Systems (ICESC)* (pp. 961–965). IEEE. https://doi.org/10.1109/ICESC48915.2020.9155588

Lai, C. H., Liu, M. C., Liu, C. J., & Huang, Y. M. (2016). Using positive visual stimuli to lighten the online learning experience through in class questioning. *The International Review of Research in Open and Distance Learning*, *17*(1), 23–41. https://doi.org/10.19173/irrodl.v17i1.2114

Lai, S., Liu, J., Niu, B., Tian, H., & Wu, F. (2019). Combining facial behavioral cues, eye movements and EEG-based attention to improve prediction of reading failure. In *2019 International Joint Conference on Information, Media and Engineering (IJCIME)* (pp. 485–489). IEEE. https://doi.org/10.1109/IJCIME49369.2019.00103

Larsen, T., Toftegaard, L. L., Mortensen, A., & Hansen, K. L. (2021). *Exploring the applicability of portable EEG technology in unmanaged classroom settings and managed group experiments*. https://www.ucviden.dk/ws/portalfiles/portal/138187647/EEG_recording_and_feedback_in_the_classroom_Submitted.pdf

Lau-Zhu, A., Lau, M. P. H., & McLoughlin, G. (2019). Mobile EEG in research on neurodevelopmental disorders: Opportunities and challenges. *Developmental Cognitive Neuroscience*, *36*, 100635. https://doi.org/10.1016/j.dcn.2019.100635

Lee, P. J., & Chin, S. W. (2014). Early childhood educator assistant with brain computer interface. In *International Conference on Software Intelligence Technologies and Applications and International Conference on Frontiers of Internet of Things 2014* (pp. 52–57). IET. https://doi.org/10.1049/cp.2014.1535

Lee, S., Cho, H., Kim, K., & Jun, S. C. (2019). Simultaneous EEG acquisition system for multiple users: Development and related issues. *Sensors*, *19*(20), 4592. https://doi.org/10.3390/s19204592

Li, G. L., Wu, J. T., Xia, Y. H., He, Q. G., & Jin, H. G. (2020). Review of semi-dry electrodes for EEG recording. *Journal of Neural Engineering*, *17*(5), 051004. https://doi.org/10.1088/1741-2552/abbd50

Li, Y., Li, S., Gao, W., Xu, W., Xu, Y., & Wang, J. (2022). Exploring the effects of indoor temperature on college students' physiological responses, cognitive performance and a concentration index derived from EEG signals. *Developments in the Built Environment*, *12*, 100095. https://doi.org/10.1016/j.dibe.2022.100095

Lin, F.-R., & Kao, C.-M. (2018). Mental effort detection using EEG data in E-learning contexts. *Computers and Education*, *122*, 63–79. https://doi.org/10.1016/j.compedu.2018.03.020

Lin, H. C. K., Su, S. H., Chao, C. J., Hsieh, C. Y., & Tsai, S. C. (2016). Construction of multi-mode affective learning system: Taking affective design as an example. *Journal of Educational Technology and Society*, *19*(2), 132–147. https://www.jstor.org/stable/jeductechsoci.19.2.132

Lin, Y. T., & Chen, C. M. (2019). Improving effectiveness of learners' review of video lectures by using an attention-based video lecture review mechanism based on brainwave signals. *Interactive Learning Environments*, *27*(1), 86–102. https://doi.org/10.1080/10494820.2018.1451899

Liu, N. H., Chiang, C. Y., & Chu, H. C. (2013). Recognizing the degree of human attention using EEG signals from mobile sensors. *Sensors*, *13*(8), 10273–10286. https://doi.org/10.3390/s130810273

Liu, Y., & Zhang, Y. (2021). Developing sustaining authentic partnership between MBE researchers and local schools. *Mind, Brain, and Education*, *15*(2), 153–162. https://doi.org/10.1111/mbe.12280

Makransky, G., Terkildsen, T. S., & Mayer, R. E. (2019). Adding immersive virtual reality to a science lab simulation causes more presence but less learning. *Learning and Instruction*, *60*, 225–236. https://doi.org/10.1016/j.learninstruc.2017.12.007

Martinez, T., & Zhao, Y. (2018). The impact of mindfulness training on middle grades students' office discipline referrals. *RMLE Online*, *41*(3), 1–8. https://doi.org/10.1080/19404476.2018.1435840

Maskeliunas, R., Damasevicius, R., Martisius, I., & Vasiljevas, M. (2016). Consumer-grade EEG devices: Are they usable for control tasks? *PeerJ*, *4*, e1746. https://doi.org/10.7717/peerj.1746

Mason, L. (2009). Bridging neuroscience and education: A two-way path is possible. *Cortex*, *45*(4), 548–549. https://doi.org/10.1016/j.cortex.2008.06.003

Mathewson, K. E., Harrison, T. J., & Kizuk, S. A. (2017). High and dry? Comparing active dry EEG electrodes to active and passive wet electrodes. *Psychophysiology*, *54*(1), 74–82. https://doi.org/10.1111/psyp.12536

Matusz, P. J., Dikker, S., Huth, A. G., & Perrodin, C. (2019). Are we ready for real-world neuroscience? *Journal of Cognitive Neuroscience*, *31*(3), 327–338. https://doi.org/10.1162/jocn_e_01276

Mazher, M., Abd Aziz, A. B., Malik, A. S., & Qayyum, A. (2015, November). A comparison of brain regions based on EEG during multimedia learning cognitive activity. In *2015 IEEE Student Symposium in Biomedical Engineering & Sciences (ISSBES)* (pp. 31–35). IEEE. https://doi.org/10.1109/ISSBES.2015.7435888

Meza, C. E. R., Manrique, M. A. V., & Quijano, F. E. S. (2018, May). Applicability of Neurofeedback for attention capacity in a school environment. In *2018 IX International Seminar of Biomedical Engineering (SIB)* (pp. 1–6). IEEE. https://doi.org/10.1109/SIB.2018.8467755

Mohamed, Z., El Halaby, M., Said, T., Shawky, D., & Badawi, A. (2018). Characterizing focused attention and working memory using EEG. *Sensors*, *18*(11), 3743. https://doi.org/10.3390/s18113743

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & PRISMA Group. (2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *PLoS Medicine*, *6*(7), e1000097. https://doi.org/10.1371/journal.pmed.1000097

Moldovan, A. N., Ghergulescu, I., & Muntean, C. H. (2017). Análisis del interés del alumno, QoE y estados afectivos basados en EEG en el aprendizaje móvil multimedia. In *2017 IEEE 17th International Conference on Advanced Learning Technologies (ICALT)* (pp. 398–402). IEEE. https://doi.org/10.1109/ICALT.2017.93

Murphy, P. K., & Benton, S. L. (2010). The new frontier of educational neuropsychology: Unknown opportunities and unfulfilled hopes. *Contemporary Educational Psychology*, *2*(35), 153–155. https://doi.org/10.1016/j.cedpsych.2010.04.006

Nandi, A., Xhafa, F., Subirats, L., & Fort, S. (2021). Real-time emotion classification using EEG data stream in E-learning contexts. *Sensors*, *21*(5), 1589. https://doi.org/10.3390/s21051589

Naumann, S., Byrne, M. L., de la Fuente, A., Harrewijn, A., Nugiel, T., Rosen, M., van Atteveldt, N., & Matusz, P. J. (2022). Assessing the degree of ecological validity of your study: Introducing the Multidimensional Assessment of Research in Context (MARC) Tool. *Mind, Brain, and Education*, *16*(3), 228–238. https://doi.org/10.1111/mbe.12318

Ni, D., Wang, S., & Liu, G. (2020). The EEG-based attention analysis in multimedia m-learning. *Computational and Mathematical Methods in Medicine*, *2020*, 4837291. https://doi.org/10.1155/2020/4837291

Ninaus, M., Kober, S. E., Friedrich, E. V., Dunwell, I., De Freitas, S., Arnab, S., Ott, M., Kravcik, M., Lim, T., Louchart, S., Bellotti, F., Hannemann, A., Thin, A. G., Berta, R., Wood, G., & Neuper, C. (2014). Neurophysiological methods for monitoring brain activity in serious games and virtual environments: A review. *International Journal of Technology Enhanced Learning*, *6*(1), 78–103. https://doi.org/10.1504/IJTEL.2014.060022

Pajk, T., Van Isacker, K., Aberšek, B., & Flogie, A. (2021). STEM education in eco-farming supported by ICT and Mobile applications. *Journal of Baltic Science Education*, *20*(2), 277–288.

Patil, A. U., Madathil, D., Fan, Y. T., Tzeng, O. J. L., Huang, C. M., & Huang, H. W. (2022). Neurofeedback for the education of children with ADHD and specific learning disorders: A review. *Brain Sciences*, *12*(9), 1238. https://doi.org/10.3390/brainsci12091238

Petersen, S. E., & Posner, M. I. (2012). The attention system of the human brain: 20 years after. *Annual Review of Neuroscience*, *35*, 73–89. https://doi.org/10.1146/annurev-neuro-062111-150525

Posner, M. I., & Rothbart, M. K. (2007). *Educating the human brain*. American Psychological Association.

Poulsen, A. T., Kamronn, S., Dmochowski, J., Parra, L. C., & Hansen, L. K. (2017). EEG in the classroom: Synchronised neural recordings during video presentation. *Scientific Reports*, *7*, 43916. https://doi.org/10.1038/srep43916

Rajendran, V. G., Jayalalitha, S., & Adalarasu, K. (2022). EEG based evaluation of examination stress and test anxiety among college students. *IRBM*, *43*(5), 349–361. https://doi.org/10.1016/j.irbm.2021.06.011

Ramírez-Moreno, M. A., Díaz-Padilla, M., Valenzuela-Gómez, K. D., Vargas-Martínez, A., Tudón-Martínez, J. C., Morales-Menendez, R., Ramírez-Mendoza, R. A., Pérez-Henríquez, B. L., & Lozoya-Santos, J. J. (2021). EEG-based tool for prediction of university Students' cognitive performance in the classroom. *Brain Sciences*, *11*(6), 698. https://doi.org/10.3390/brainsci11060698

Ramos-Loyo, J., Olguín-Rodríguez, P. V., Espinosa-Denenea, S. E., Llamas-Alonso, L. A., Rivera-Tello, S., & Müller, M. F. (2022). EEG functional brain connectivity strengthens with age during attentional processing to faces in children. *Frontiers in Network Physiology*, *2*, 890906. https://doi.org/10.3389/fnetp.2022.890906

Robinson, K., Wehner, T., & Millward, H. (2019). Is the outcome of remote group work using text based CMC suboptimal? A psychobiological perspective. *Computers and Education*, *134*, 108–118. https://doi.org/10.1016/j.compedu.2019.02.009

Rose, N., & Abi-Rached, J. (2014). Governing through the brain: Neuropolitics, neuroscience and subjectivity. *The Cambridge Journal of Anthropology*, *32*(1), 3–23. https://doi.org/10.3167/ca.2014.320102

Santamaría-Vázquez, E., Martínez-Cagigal, V., Marcos-Martínez, D., Rodríguez-González, V., Pérez-Velasco, S., Moreno-Calderón, S., & Hornero, R. (2023). MEDUSA©: A novel python-based software ecosystem to accelerate brain-computer interface and cognitive neuroscience research. *Computer Methods and Programs in Biomedicine*, *230*, 107357. https://doi.org/10.1016/j.cmpb.2023.107357

Scholkmann, F., Kleiser, S., Metz, A. J., Zimmermann, R., Mata Pavia, J., Wolf, U., & Wolf, M. (2014). A review on continuous wave functional near-infrared spectroscopy and imaging instrumentation and methodology. *NeuroImage*, *85*(Pt 1), 6–27. https://doi.org/10.1016/j.neuroimage.2013.05.004

Seghier, M. L., Fahim, M. A., & Habak, C. (2019). Educational fMRI: From the lab to the classroom. *Frontiers in Psychology*, *10*, 2769. https://doi.org/10.3389/fpsyg.2019.02769

Seok, D., Lee, S., Kim, M., Cho, J., & Kim, C. (2021). Motion artifact removal techniques for wearable EEG and PPG sensor systems. *Frontiers in Electronics*, *2*, 685513. https://doi.org/10.3389/felec.2021.685513

Sethi, C., Dabas, H., Dua, C., Dalawat, M., & Sethia, D. (2018). EEG-based attention feedback to improve focus in E-learning. In *Proceedings of the 2018 2nd International Conference on Computer Science and Artificial Intelligence* (pp. 321–326). https://doi.org/10.1145/3297156.3297157

Sezer, A., Inel, Y., Seçkin, A. Ç., & Uluçinar, U. (2017). The relationship between attention levels and class participation of first-year students in classroom teaching departments. *International Journal of Instruction*, *10*(2), 55–68. https://files.eric.ed.gov/fulltext/EJ1138334.pdf

Shad, E. H. T., Molinas, M., & Ytterdal, T. (2020). Impedance and noise of passive and active dry EEG electrodes: A review. *IEEE Sensors Journal*, *20*(24), 14565–14577. https://doi.org/10.1109/JSEN.2020.3012394

Shadiev, R., & Huang, Y.-M. (2020). Investigating student attention, meditation, cognitive load, and satisfaction during lectures in a foreign language supported by speech-enabled language translation. *Computer Assisted Language Learning*, *33*(3), 301–326. https://doi.org/10.1080/09588221.2018.1559863

Shamay-Tsoory, S. G., & Mendelsohn, A. (2019). Real-life neuroscience: An ecological approach to brain and behavior research. *Perspectives on Psychological Science*, *14*(5), 841–859. https://doi.org/10.1177/1745691619856350

Siripornpanich, V., Sampoon, K., Chaithirayanon, S., Kotchabhakdi, N., & Chutabhakdikul, N. (2018). Enhancing brain maturation through a mindfulness-based education in elementary school children: A quantitative EEG study. *Mindfulness*, *9*(6), 1877–1884. https://doi.org/10.1007/s12671-018-0930-3

Sonkusare, S., Breakspear, M., & Guo, C. (2019). Naturalistic stimuli in neuroscience: Critically acclaimed. *Trends in Cognitive Sciences*, *23*(8), 699–714. https://doi.org/10.1016/j.tics.2019.05.004

Sorochinsky, M., Koryakin, P., & Popov, M. (2022). A study of students' attention levels while watching educational videos with the use of neurofeedback. In *2022 Fourth International Conference Neurotechnologies and Neurointerfaces (CNN)* (pp. 165–167). IEEE. https://doi.org/10.1109/CNN56452.2022.9912564

Sulaiman, N., Ismail, N., Islam, M. N., Rashid, M., Jadin, M. S., Mustafa, M., & Samsuri, F. (2022). Development of EEG-based system to identify student learning attention ability. In *Proceedings of the 12th National Technical Seminar on Unmanned System Technology 2020* (pp. 627–639). Springer.

Sun, J. C.-Y. (2014). Influence of polling technologies on student engagement: An analysis of student motivation, academic performance, and brainwave data. *Computers and Education*, *72*, 80–89. https://doi.org/10.1016/j.compedu.2013.10.010

Sun, J. C.-Y., & Yeh, K. P.-C. (2017). The effects of attention monitoring with EEG biofeedback on university students' attention and self-efficacy: The case of anti-phishing instructional materials. *Computers and Education*, *106*, 73–82. https://doi.org/10.1016/j.compedu.2016.12.003

Suttidee, A., & Ruanguttamanun, C. (2022). Do you think your students are into online learning? Brain responses using electroencephalography. *Creative Business and Sustainability Journal*, *44*(2), 80–94. https://so01.tci-thaijo.org/index.php/CBSReview/article/view/263672

Tang, H., Dai, M., Du, X., Hung, J. L., & Li, H. (2023). An EEG study on college students' attention levels in a blended computer science class. *Innovations in Education and Teaching International*, *61*, 789–801. https://doi.org/10.1080/14703297.2023.2166562

Tinga, A. M., de Back, T. T., & Louwerse, M. M. (2020). Non-invasive neurophysiology in learning and training: Mechanisms and a SWOT analysis. *Frontiers in Neuroscience*, *14*, 589. https://doi.org/10.3389/fnins.2020.00589

Upadhyay, R., Singh, M., Mishra, S., Mehta, J., Bansal, A., Baranwal, M., & Kumar, V. (2022). Electroencephalogram Data Collection for Student Engagement Analysis with Audio-Visual Content. *bioRxiv*. https://doi.org/10.1101/2022.09.20.508656

Van Atteveldt, N., Van Kesteren, M. T. R., Braams, B., & Krabbendam, L. (2018). Neuroimaging of learning and development: Improving ecological validity. *Frontline Learning Research*, *6*(3), 186–203. https://doi.org/10.14786/flr.v6i3.366

Vandermosten, M., Hoeft, F., & Norton, E. S. (2016). Integrating MRI brain imaging studies of pre-reading children with current theories of developmental dyslexia: A review and quantitative meta-analysis. *Current Opinion in Behavioral Sciences*, *10*, 155–161. https://doi.org/10.1016/j.cobeha.2016.06.007

Varma, S., McCandliss, B. D., & Schwartz, D. L. (2008). Scientific and pragmatic challenges for bridging education and neuroscience. *Educational Researcher*, *37*(3), 140–152. https://doi.org/10.3102/0013189X08317687

Varnavsky, A. N., & Romanova, I. I. (2020). Using brain-computer interface for measuring indicators of cognitive processes (a case of doing educational Reading). In *2020 IEEE 40th International Conference on Electronics and Nanotechnology (ELNANO)* (pp. 484–487). IEEE. https://doi.org/10.1109/ELNANO50318.2020.9088759

Vasiljevic, G. A. M., & de Miranda, L. C. (2020). Brain–computer interface games based on consumer-grade EEG devices: A systematic literature review. *International Journal of Human-Computer Interaction*, *36*(2), 105–142. https://doi.org/10.1080/10447318.2019.1612213

Vekety, B., Logemann, A., & Takacs, Z. K. (2022). Mindfulness practice with a brain-sensing device improved cognitive functioning of elementary school children: An exploratory pilot study. *Brain Sciences*, *12*(1), 103. https://doi.org/10.3390/brainsci12010103

Verkijika, S. F., & De Wet, L. (2015). Using a brain-computer interface (BCI) in reducing math anxiety: Evidence from South Africa. *Computers and Education*, *81*, 113–122. https://doi.org/10.1016/j.compedu.2014.10.002

Veronica, F., Gunawan, H., Fitri, L. L., Fernando, A., Nadhova, G., & Hilsa, H. (2022). Simple EEG assess working memory process in difference gender. *Jurnal Kedokteran Dan Kesehatan*, *9*(3), 339–344. https://doi.org/10.32539/JKK.V9I3.18914

Waisman, I., Brunner, C., Grabner, R. H., Leikin, M., & Leikin, R. (2023). (lack of) neural efficiency related to general giftedness and mathematical excellence: An EEG study. *Neuropsychologia*, *179*, 108448. https://doi.org/10.1016/j.neuropsychologia.2022.108448

Wang, J., Antonenko, P., Keil, A., & Dawson, K. (2020). Converging subjective and psychophysiological measures of cognitive load to study the effects of instructor-present video. *Mind, Brain, and Education*, *14*(3), 279–291. https://doi.org/10.1111/mbe.12239

Webster, J., & Watson, R. T. (2002). Analyzing the past to prepare for the future: Writing a literature review. *MIS Quarterly*, *26*, xiii–xxiii.

Willems, R. M., Nastase, S. A., & Milivojevic, B. (2020). Narratives for neuroscience. *Trends in Neurosciences*, *43*(5), 271–273. https://doi.org/10.1016/j.tins.2020.03.003

Williamson, B. (2018). Brain data: Scanning, scraping and sculpting the plastic learning brain through Neurotechnology. *Postdigital Science and Education*, *1*, 65–86. https://doi.org/10.1007/s42438-018-0008-5

Willingham, D. T. (2009). Three problems in the marriage of neuroscience and education. *Cortex*, *45*(4), 544–545. https://doi.org/10.1016/j.cortex.2008.05.009

Xiaojun, Z., Xinrui, K., & Xupeng, L. (2022). The influence of learning mode and learning sharing behavior on the synchronicity of attention of sharers and learners. *BMC Psychology*, *10*(1), 166. https://doi.org/10.1186/s40359-022-00871-z

Xu, J., & Zhong, B. (2018). Review on portable EEG technology in educational research. *Computers in Human Behavior*, *81*, 340–349. https://doi.org/10.1016/j.chb.2017.12.037

Xu, K., Torgrimson, S. J., Torres, R., Lenartowicz, A., & Grammer, J. K. (2022). EEG data quality in real-world settings: Examining neural correlates of attention in school-aged children. *Mind, Brain, and Education*, *16*(3), 221–227. https://doi.org/10.1111/mbe.12314

Yang, X., Zhao, X., Tian, X., & Xing, B. (2020). Effects of environment and posture on the concentration and achievement of students in mobile learning. *Interactive Learning Environments*, *29*(3), 400–413. https://doi.org/10.1080/10494820.2019.1707692

Yao, S., Zhu, J., Li, S., Zhang, R., Zhao, J., Yang, X., & Wang, Y. (2022). Bibliometric analysis of quantitative electroencephalogram research in neuropsychiatric disorders from 2000 to 2021. *Frontiers in Psychiatry*, *13*, 830819. https://doi.org/10.3389/fpsyt.2022.830819

Yu, Z., Zhao, H., Guo, C., Guo, J., Zhang, S., Hu, K., & Chen, Z. (2020, May). A LSTM network-based Learners' monitoring model for academic self-efficacy evaluation using EEG signal analysis. In *2020 5th IEEE International Conference on Big Data Analytics (ICBDA)* (pp. 154–159). IEEE. https://doi.org/10.1109/ICBDA49040.2020.9101313

Zhan, Z., Yang, Q., Luo, L., & Zhang, X. (2024). Applying functional near-infrared spectroscopy (fNIRS) in educational research: A systematic review. *Current Psychology*, *43*(11), 9676–9691. https://doi.org/10.1007/s12144-023-05094-y

Zhang, S., Yan, Z., Sapkota, S., Zhao, S., & Ooi, W. T. (2021). Moment-to-moment continuous attention fluctuation monitoring through consumer-grade EEG device. *Sensors*, *21*(10), 3419. https://doi.org/10.3390/s21103419

Zheng, X., Ma, Y., Yue, T., & Yang, X. (2023). Effects of different types of cues and self-explanation prompts in instructional videos on deep learning: Evidence from multiple data analysis. *Educational Technology Research and Development*, *71*, 807–831. https://doi.org/10.1007/s11423-023-10188-2

Zhou, Y., Xu, T., Cai, Y., Wu, X., & Dong, B. (2017). Monitoring cognitive workload in online videos learning through an EEG-based brain-computer interface. In *Learning and collaboration technologies. Novel learning ecosystems: 4th international conference, LCT 2017, held as part of HCI international 2017, Vancouver, BC, Canada, July 9–14, 2017, proceedings, part I 4* (pp. 64–73). Springer International Publishing. https://doi.org/10.1007/978-3-319-58509-3_7

Zhu 朱怡, Y., Pan 潘亚峰, Y., & Hu 胡谊, Y. (2019). Learning desire is predicted by similar neural processing of naturalistic educational materials. *eNeuro*, *6*(5), ENEURO.0083-19.2019. https://doi.org/10.1523/ENEURO.0083-19.2019

How to cite this article: García-Monge, A., Rodríguez-Navarro, H., Bores-García, D., & González-Calvo, G. (2024). Electroencephalography in naturalistic and semi-naturalistic educational contexts: A systematic review. *Review of Education*, *12*, e70020. https://doi.org/10.1002/rev3.70020