



On enhancing students' cognitive abilities in online learning using brain activity and eye movements

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Abstract

The COVID-19 pandemic has interrupted education institutions in over 150 nations, affecting billions of students. Many governments have forced a transition in higher education from in-person to remote learning. After this abrupt, worldwide transition away from the classroom, some question whether online education will continue to grow in acceptance in post-pandemic times. However, new technology, such as the brain-computer interface and eye-tracking, have the potential to improve the remote learning environment, which currently faces several obstacles and deficiencies. Cognitive brain computer interfaces can help us develop a better understanding of brain functions, allowing for the development of more effective learning methodologies and the enhancement of brain-based skills. We carried out a systematic literature review of research on the use of brain computer interfaces and eye-tracking to measure students' cognitive skills during online learning. We found that, because many experimental tasks depend on recorded rather than real-time video, students don't have direct and real-time interaction with their teacher. Further, we found no evidence in any of the reviewed papers for brain-to-brain synchronization during remote learning. This points to a potentially fruitful future application of brain computer interfaces in education, investigating whether the brains of student-teacher pairs who interact with the same course content have increasingly similar brain patterns.

Keywords Online learning · Electroencephalogram · Eye-tracking · Attention · Student-teacher interaction · Systematic literature review

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1 Introduction

Learning is a complex process with many interacting components: it may include understanding concepts; comprehending proofs; recalling factual knowledge; acquiring methods, strategies, and approaches; as well as reasoning; recognizing and debating ideas; and performing behaviors relevant to specific situations. Learning may take place in a variety of ways. It can happen throughout life, informally (e.g., learning from experience or observation without being fully aware of it, or gaining knowledge from watching the news or reading a newspaper) and formally (e.g., in classroom, with organized and structured curriculum, involving students, teachers, and an institution) (Kolb, 1976). Everything a student learns in formal education comes from books and other educational materials whose primary function is to help them learn. Most teachers are trained and licensed to teach (Darling-Hammond, 1999). Most students have the same teachers to see every day, whose steady presence keep their educational environment stable and their learning on track.

However, at the end of 2019, an epidemic of the Covid-19 virus started in Wuhan, China, and subsequently spread globally, disrupting many sectors of society, including education. The most common response of the education industry was to transform teaching and learning dramatically. At the beginning of the pandemic, most educational institutions shifted their entire teaching and learning activities to the internet. In order to mitigate the negative implications of the abrupt changes in the educational process and maintain the continuity of teaching and learning, the educational institutions put a lot of effort into converting their curriculum adequate for remote learning (Ali, 2020). During the course of the COVID-19 pandemic, nationwide attempts to use technology to promote remote learning, distance education, and online learning have been growing and expanding swiftly. However, research has identified several flaws in this transitioning, including a lack of sufficient online educational infrastructure, shortcomings of instructor incompetence, and discomfort in the new learning environment (Adeyoin, 2020). Regardless of its various limitations, the new educational scenario is indispensable and requires intervention to ensure that students' education is not jeopardized.

Students' academic performance is affected by a variety of influence factors, such as attention, cognitive load, sleep, emotion, and stress that are rooted in the cognitive and affective state of their brain (Jamil et al., 2021). There has been a lot of research done on attention, engagement, distraction, and interaction that can be used in virtual settings. For the most part, teachers in face-to-face situations demonstrate their interest in students by observing and responding to their actions. Visibility of students in a remote learning situation is limited, teachers may only be able to view the their heads and shoulders, and only if the students keep their video camera turned on. Unfortunately, many students prefer to turn off their video camera during remote learning, making it impossible for the teacher to monitor the student's attention.

The interaction between student and teacher is essential. It is natural for students to engage face-to-face with the teacher in a conversation, which facilitates

active listening and instantaneous exchange. Students' achievement, grades, and feelings of contentment are all affected by their teachers' interactions with them (Roblyer & Ekhaml, 2000). Students' academic performance may decline if they do not feel included in their academic community, which is fostered through regular academic, and social interactions (Yeager et al., 2013). According to recent research, the lack of face-to-face interaction during the Covid-19 pandemic is not only associated with a feeling of isolation, but may also be a substantial source of stress for students (Son et al., 2020; Dumitrache et al., 2021).

More recently, novel sensor technologies, such as the brain-computer interface (BCI) and eye-tracking, have started to offer innovative ways to monitor and measure student performance (Jamil et al., 2021). The electrical activity of the brain may be monitored and assessed invasively or non-invasively, in selective frequency bands tuned to different brain waves, such as alpha, beta, and theta waves. These waves carry information about a person's mental state (Gui et al., 2019; Tandle et al., 2018). The most common, non-invasive, method of obtaining an electroencephalogram (EEG) signal involves placing electrodes on a person's scalp. This approach, which is easy to implement and provides a signal of high quality at minimal cost, is suitable for education. Thus, with the aid of BCIs as a cognitive tool, the human brain may be studied to examine, comprehend, and improve the learning process. On the other hand, eye-tracking technologies might be harnessed in the virtual educational environment to generate process cues in complicated visual tasks. Eye-tracking is a technique for measuring eye movements to determine the direction of a person's gaze and the sequence and duration of its deployment, which can help to infer the student's engagement. While eye-tracking is commonly employed to study visual behavior, it might also be utilized as an educational tool to enhance task performance and learning (Jarodzka et al., 2021).

In the physical classroom, EEG headbands have already been used to assess students' cognitive abilities such as reading, learning, attention, and memory (Ramírez-Moreno, 2021; Ko et al., 2017). In contrast, and to the best of our knowledge, neuroscience experiments using EEG in a remote learning environment has not yet been done. Because of Covid-19, remote learning has become the major choice for education and has been practiced exclusively or in an approach mixed with in-person periods. Remote learning can be structured similarly to traditional learning, with the instructor as the primary source of knowledge. In this form, remote learning is reliant on real-time interactions between students and teachers. To evaluate students' interaction with remote learning, methods commonly used in education, psychology, and behavioral sciences as well as theoretical concepts are used frequently. The efficacy of these constructs is constantly evaluated using both qualitative and quantitative methodologies (Fazza & Mahgoub, 2021; Aguilera-Hermida, 2020). This approach has its weaknesses. The responses may contain biases and are dependent on human inference. Furthermore, face-to-face interactions moderate the relationship between social factors and brain-to-brain synchronization. Pairs of students who participated in face-to-face interaction had better paired neural synchronicity during class, which can affect student engagement and achievement (Dikker et al., 2017). However, brain synchronization between teachers and students during remote learning remains to be explored.

With this background, we aimed our systematic literature review (SLR) to investigations of students' cognitive abilities and interactions in the remote learning environment to address the following three sets of research questions (RQs):

- **RQ1:** How to measure the cognitive abilities of students in the remote learning environment?
- **RQ2:** How to improve students' learning in the remote learning environment?
- **RQ3:** How to evaluate the student interaction in the absence of student-teacher eye contact?

Therefore, this SLR provides significant contributions by attempting to fill several background problems. This thought inspired this SLR of scientific studies to better understand brain function and eye movement by combining BCI and eye-tracking technologies. This SLR may result in a new brain- and eye-patterns-based online educational pedagogy. The review aims to critically examine and review the scientific literature on students' cognitive abilities. The preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Liberati et al., 2009) method is employed to increase the transparency of systematic reviews.

2 Literature Review

2.1 Student's cognitive abilities

The evaluation of cognitive ability is one of the most important aspects of the learning process. Cognitive abilities are based on brain functions and required for all activities, from the easiest to the most challenging. They are especially involved with the activities of learning, remembering, and problem-solving, as well as paying attention (Plomin, 1999). Cognitive capacities are thought of as the accelerator for goal-oriented learning, with a positive influence on academic achievement (Winne & Nesbit, 2010). Since teacher instruction and feedback are the key sources of information for students in the acquisition of their cognitive skills and practices, teachers are believed, by implication, to be aware of their students' cognitive skills. It is therefore imperative that unfavorable information be avoided, while rapid evaluations and actions are anticipated to stimulate the development of cognitive capacities. To realize this imperative, instructors need to pay close attention to monitor the development of their students' cognitive abilities, which may vary from student to student. To better comprehend students' specific needs, investigators have started to focus on how students learn in an online setting, with special emphasis on student involvement in online learning (Chiu, 2022), students' memory (Giusti et al., 2021), and their emotional and behavioral patterns throughout their academic careers (Hewson, 2018).

One critical goal in remote learning is maintaining the student's attention, which is the initial stage in the learning process. While the human brain is extremely effective at processing information, it has a finite capacity, which means it cannot respond to all external inputs and memories simultaneously.

Time management and organizing the study environment are key to focus one's mind on the academic subject at hand, to avoid distractions while performing the task required to achieve the academic goal (Kwon et al., 2018).

The pandemic has made it hard for students to participate in class face-to-face with their teacher. One commonly adopted alternative was to provide recorded lectures for the students to listen to later offline or in an online learning setting. However, if the student is distracted and doesn't pay attention, the information will be lost to them (information not stored in their memory will not be possible to retrieve later). Thus, student distraction and a lack of attention has become the primary issue to manage. A further problem with remote learning is that the instructor is unaware of how students comprehend the material presented.

Being competent to pay attention to the work at hand is critical for academic achievement (Anastopoulos & King, 2015). It is well recognized that, despite the benefits provided by technology, students continue to struggle to retain their focus on the content being delivered to them Cicekci & Sadik (2019). The consequences of shortened attention span and decreased levels of concentration are felt more acutely in online learning, where the learning process becomes less effective. Furthermore, during remote learning, students may not have a feeling of cognitive engagement and social connection, which might have a detrimental effect on their learning results (Bower, 2019). A student who was free of distractions earned a better GPA than students who did not Kitsantas et al. (2008).

In the traditional classroom, students have numerous opportunities to communicate with their teachers and this interaction is crucial to student achievement. It is difficult enough to compel students to take part and interact in class activities in a face-to-face classroom, but it is a great deal more challenging in a virtual classroom. In a remote learning session, the social pressure of making unpleasant eye contact is absent. Technology influences the interaction between students and teachers, and the design of learning environments may have a significant impact on learning results (Bower, 2019; Gonzalez et al., 2020).

Student interaction is a critical component of any style of learning, but it is especially crucial in the remote learning environment (Bernard et al., 2009; Eom et al., 2006). Typically, under a the face-to-face engagement in the classroom, the teacher's focus is on lecturing, examining, instructing, and interacting with students. In contrast, in the remote learning setting, the teacher would likely lose this direct connection since students would interact with various online learning tools rather than the teacher. Students who do not have significant engagement with the teacher may feel detached and demotivated. In fact, social interaction in remote learning may boost student engagement and motivation and assist students in performing better. Higher levels of learning and satisfaction were indicated by students who believed they had more interaction with the teacher than by students who had fewer interactions (Swan, 2001). The active presence of a teacher who actively controls, supervises and guides the discussion, has a favorable impact on both the students' sense of connectivity and their learning (Shea et al., 2006).

2.2 Measuring students' cognitive abilities

There are specific techniques for measuring the students' cognitive abilities, ranging from subjective to direct and indirect objective measures (Martin, 2014). The most common subjective measures currently in use are: (a) questionnaires for self-reports by students, (b) questionnaires to teachers about students, and (c) performance tests (Duckworth & Yeager, 2015). Self-reporting and questionnaires are the simplest and quickest data collection methods. A large body of evidence accumulated in social and cognitive psychology research reveals that people are generally adept at conveying their real thoughts when filling questionnaires, assuming they have answers to those questions and are satisfied reporting them truthfully (Krosnick, 1999). Performance tests employ several approaches to evaluating students' cognitive performance, including informal methods to complete a task in a brief oral quiz or in brief written responses, and formal methods, such as the final written examination.

However, the subjective measures have some limitations. Self-reports are susceptible to biases, such as stemming from the perceived pressures of social desirability, in which students feel the need to appear good while answering the questions. Thus, students may provide a socially acceptable response rather than the truth. Similarly, there are biases associated with teachers' questionnaires. For example, teachers, unlike parents who see the students in every situation outside school, only observe the students in the classroom and may misinterpret student actions because of their limited perceptions (Achenbach et al., 1987).

Examples of objective measures include eye-tracking and brain activity measures employing neuroimaging techniques, such as Functional Near-infrared Spectroscopy (fNIRS), Functional Magnetic Resonance Imaging (fMRI), electrocorticography (ECoG), magnetoencephalography (MEG), and EEG (Dahlstrom-Hakki et al., 2019). The fNIRS is non-invasive, with its sensors detecting even the smallest variations in the light to quantify changes in the concentration of oxygenated and deoxygenated hemoglobin. However, this method is incapable of providing information on brain anatomy, and the inter-subject variation of the sensitivity of fNIRS might be affected by differences in the thickness of the skull and the composition of sculp tissues, especially in adults (Chen et al., 2020). fMRI also detects changes in blood oxygenation levels between the states of different activations of the brain. However, it is sensitive to brain activity at any depth and has good enough spatial resolution to locate regions of activity. fMRI has become the primary imaging tool to identify areas of the brain that are activated in response to performing a particular cognitive activity. However, fMRI is expensive, and it is very susceptible to imaging artifacts from the small movements.

The MEG detects changes in the magnetic fields created by neural activity in the brain can be used, as fMRI, to create a functional map of the brain and exactly pinpoint the areas of the highest brain activity, but with much higher temporal resolution than in fMRI. However, this method is similarly expensive and sensitive to movement artifacts. In contrast, ECoG and EEG are much less expensive and both are used to monitor the gross average activity of millions of neurons with high temporal and low spatial resolution, with the results often presented in the form of temporal variations of oscillatory waves. However, ECoG is invasive, requiring surgery

to place the ECoG electrode array underneath the scalp. Because of this, ECoG is not appropriate for students who do not already have an appointment set for a medical procedure that includes opening the scalp. Because of the practical limitations associated with many methods as discussed above, this SLR only focuses on EEG and eye-tracking to measure students' cognitive abilities in the remote learning environment.

2.2.1 Measuring cognitive abilities with EEG

Neuroscience research is being conducted in a wide range of cognitive areas. Learning involves several neurocognitive processes, including memory, information processing, and attention, which play a role in determining the results of educational activity. BCIs can be used to get direct access to the neurocognitive processes involved in learning and have the potential to monitor these processes and help bring educational procedures to entirely new levels. One example is BCIs being used to determine students' cognitive load by measuring their cognitive states. EEG, the most widely used technology for assessing brain activity, has been used with consistent success in the investigation of cognitive load (Hsu, 2021; Pi et al., 2021; Liu, 2021).

The level of attention substantially impacts students' learning outcomes. Teachers in the traditional face-to-face environment can monitor their students' faces to see if they are paying attention. This strategy is difficult to implement in the remote learning environment. However, in this environment, BCIs, by providing information via motor commands and complicated cognitive features, can be a tool to aid monitoring students' attention (Mohammadpour, 2017; Lim et al., 2012; Aggarwal et al., 2021; Hocine, 2021). For example, an attention aware system was developed to help the teacher monitor students' attention levels using EEG data in an e-learning environment (Chen et al., 2017). In a different approach, some researchers use computer games as a task to evaluate the students' attention, especially for those with attention deficit hyperactivity disorder (ADHD) (Lim et al., 2019; Shereena et al., 2019). The success of this approach might be because of the games being engaging, enjoyable, and entertaining.

Areas on the scalp that are favorable for detecting attention-related EEG signals were discovered by Yaomane et al. (2012). To determine whether the subjects were paying attention, these investigators conducted experiments involving three tasks: (i) identifying 3D figures, (ii) reading books, and (iii) completing questionnaires. Independently, Li et al. (2010) identified students' level of attention based on alpha and theta waves in EEG records using k-nearest neighbor (kNN) and naive Bayesian classification. In yet another approach, Sethi (2018) developed a tool to improve a student's attention using EEG-based neurofeedback while the subject was performing a reading task.

In addition to attention, student interaction is another important influence factors in any style of learning, particularly in e-learning Bernard et al. (2009). When an individual is engaged in cognitive processing activities, synchronous neural activity is firmly established. Hyperscanning (data collection methods that relate the neural activity of two individual brain areas) has been used to demonstrate that face-to-face

interactions modulate the association between social variables and brain-to-brain synchrony Jiang et al. (2015); Scholkmann et al. (2013). Among two interacting individuals, the coordination patterns of interaction reveal theta and alpha wave synchronization in the same temporal and lateral-parietal areas of the two persons Kawasaki et al. (2013). The degree of synchronization was examined for both couples and two strangers by Kinreich et al. (2017) who reported that the synchronized release of adrenaline established a paradigm for partner engagement.

Inter-brain synchronization was also discovered in another interpersonal behavioral experiment that involved cooperative and competitive activity, showing that the inter-brain synchronization between two individuals was much higher when two cooperated than when they competed Davis et al. (2016). Similarly, to investigate social interaction between teachers and students in the classroom, Bevilacqua et al. (2019) used EEG in task-based biology sessions and reported that students with more social closeness to the instructor had better brain-to-brain synchronization and a resemblance between brain regions during the social interaction. Taken together, these studies suggest that the teacher can enhance their teaching methods by directly or indirectly engaging with the students to understand their involvement and engagement with the content.

2.2.2 Measuring cognitive abilities with eye-tracking

The most widely used technique for automated attention tracking is eye tracking. Research has solidly established that attention is associated with eye movements, gaze direction, and visual fixation. For instance, a student's gaze following the teacher's directions likely indicates that the student is cognitively engaged in the learning process. Eye-tracking was applied to monitor the visual fixation of the student's gaze while answering multiple-choice questions on the computer (Tsai et al., 2012). The result showed that the students who successfully solved the tasks were more visually concentrated on areas of diagrams related to the problem. Meanwhile, in a study to monitor students' attention during a lecture, Moreno-Esteva & Hannula (2015) used gaze tracking to explore how students' gaze shifted in response to the teacher's gaze, voice, and gesture signals. In a similar study, Hutt et al. (2017) used consumer-grade eye-tracking to monitor students' mind wandering while viewing a recorded lecture.

Researchers have been investigating the notion of "student-teacher co-attention" in video lectures utilizing eye-tracking to acquire deeper insights into students' attention patterns (Sharma et al., 2020; Sinha, 2014). A gaze-based metric, known as "with-me-ness" (student following the lectures), to assess the level of co-attention between the teacher giving a talk and the students' gaze used to reveal a positive association between with-me-ness and students' learning outcome (Sinha, 2014). To address the drop of attention issue during lecture video viewing in a massive open online course (MOOC), the IntelliEye eye-tracking device was proposed to assist students in self-regulating their learning abilities (Robal, 2019).

Hocine (Hocine (2021)) proposed gamification elements in MOOC to enhance the student's attention based on eye-tracking and the real-time interaction with the resource. This study aimed for the student to interact with others in discussion form to boost their engagement. Somewhat differently, Chuang & Liu (2012) used

eye-tracking to investigate how students interacted with the learning materials, in which information is delivered in text and visual forms on a single webpage and, based on the results, gave recommendations for instructional design of multimedia learning environments.

Pouta et al. (2021) monitored teachers' eye movements to study student-teacher interaction during arithmetic class and reported that experienced teachers made more gaze movements from the teaching materials to the student's face and then back to the teaching materials. Meanwhile, Haataja et al. (2021) investigated the relationship between teachers' interpersonal behavior and direct eye contact by tracking the eye movements of both students and teachers during learning in the classroom. The findings revealed that both the teacher's and students' gaze behavior were related to the teacher's interpersonal behavior. Both of these studies used the technique of eye-tracking to investigate how experienced teachers interact with students in real teaching scenarios.

2.3 Improve students' cognitive abilities

A student's ability to learn may be improved by proper instruction, which can also help students learn more effectively. In this regard, well-organized training has proven to be most beneficial. Training of cognitive abilities that is both efficient and effective involves undivided attention and the provision of instant feedback. One of the training techniques to improve students' cognition is repetition. Memory performance can be enhanced and maintained for a long time after repetitive learning Ebbinghaus et al. (1913). A cognitive skill, with enough repetition, can eventually become a stored routine. The student understands what skill they lack and focuses on activities that will help them develop that skill. When a skill is practiced or rehearsed time and again, the activities become easier and more convenient to perform and become permanently stored for recall and use.

Previous research has found that repetition enhancement occurs during memory encoding and retrieval. Jape et al. (2022) believed the repetition approach using the flashcard could improve the skills of medical students, while some other researcher showed that repetition using interactive multimedia increased the student learning outcome (Sutarno et al., 2018). Each time the number of repetitions increased, at least one aspect of knowledge exhibited significant improvements (Webb, 2007). According to findings from behavioral research, once students were taught words and word pairs three or six times (repetition), their associative recognition skills greatly improved (Yang et al., 2016).

Feedback is also one of the techniques to increase students' cognitive abilities. The brain values and prioritizes immediate associations. Items that are closely and repeatedly associated has stronger mental connections. These types of proximity associations can be provided by immediate feedback. Positive feedback and corrective feedback are required for good brain training and are critical components of effective learning by providing clear guidance on how to improve their knowledge. Students actively engaging with feedback are expected to increase their learning and assessment performance (Race, 2001).

Teachers have been identified as key facilitators in improving student feedback through curriculum design, mentoring, and coaching (Carless & Boud, 2018). Yang & Lu (2021) have shown that students who are willing to spend time to read the feedback on their misunderstandings are more likely to improve their learning effectiveness. The summative and formative assessment should be used to determine learning outcomes and provide learners with relevant feedback that they may utilize to affect their future performance (Watling & Ginsburg, 2019; Wanner & Palmer, 2018). In summary, any assessment that includes feedback helps enhance students' cognitive and academic performance.

Consequently, this SLR had a special focus to select studies that implemented feedback or neurofeedback. Neurofeedback is a technique of biofeedback that uses real-time feedback from brain activity to promote healthy brain function. During a neurofeedback session, the brain “learns” how to bring abnormal waves back into the normal range for a certain task. For instance, the brain waves shift into the quirky range when a student becomes distracted. Feedback is given via an indicator, such as a blinking spot, on the screen facing the student, ‘encouraging’ the student’s brain to shift its oscillations back into the ideal range.

2.4 Education

There are a number of different educational theories that have been proposed and developed over the years. Each theory has its benefits and drawbacks, and each has been influential in shaping the way education is delivered today. The basic education theory is cognitivism, behaviourism, and constructivism (Ertmer & Newby, 2013). Cognitivism is a theory that focuses on the cognitive aspects of learning. This theory emphasizes the importance of understanding and remembering information, and it believes that students can learn most effectively by studying material relevant to their interests and experiences.

Behaviourism is a theory that emphasizes the role of conditioning in learning. It suggests that all behavior is a result of conditioning and that behaviour can be controlled through the use of rewards and punishments. Constructivism is a theory that emphasises individuals' role in shaping their learning experience. It suggests that knowledge is not static and that it can be modified through the use of feedback and collaboration. Three theories have their strengths and weaknesses, and it is important to weigh them against each other before deciding which education theory to use. Ultimately, the choice of education theory depends on the specific needs of the students being taught (Pritchard, 2017).

Teachers are in a better position to make decisions concerning how to approach their pedagogical practices when they have a working understanding of various theoretical perspectives (Anderson & Holt-Reynolds, 1995). Some students learn more effectively when they can work at their own pace, without the pressure of exams or other external deadlines. Online learning allows for this flexibility, as students can access materials at their convenience and take any number of breaks during class sessions.

There are a number of advantages to using online methods of learning. First, students can get the same quality of instruction they would receive in a traditional classroom setting, but without the inconvenience of having to travel to class or miss important work commitments. Second, online courses are often less expensive than traditional college courses (Yuhanna et al., 2020). Finally, online learning allows students unable to attend classes in person to receive a quality education still.

Despite these advantages, there are some drawbacks to online learning. First, many online courses do not offer the same level of interactivity and feedback available in traditional classrooms (Dumford & Miller, 2018). Second, students may feel less engaged when they cannot engage directly with the instructor or other classmates. Finally, many online courses do not have an equivalent curriculum to traditional courses, making it difficult for students to know what they are taking and how it will contribute to their overall education.

Therefore one potential application of BCIs technology is online learning. Currently, most online courses rely on static images or videos to teach students about the subject matter. BCIs technology can be used to monitor and understand students' brain activity in real-time. This can help to identify and reduce stressors during online learning, as shown in Fig. 1. Furthermore, BCIs technology can provide feedback to students about their mental health and could help students understand their own emotions and learn how to manage them.

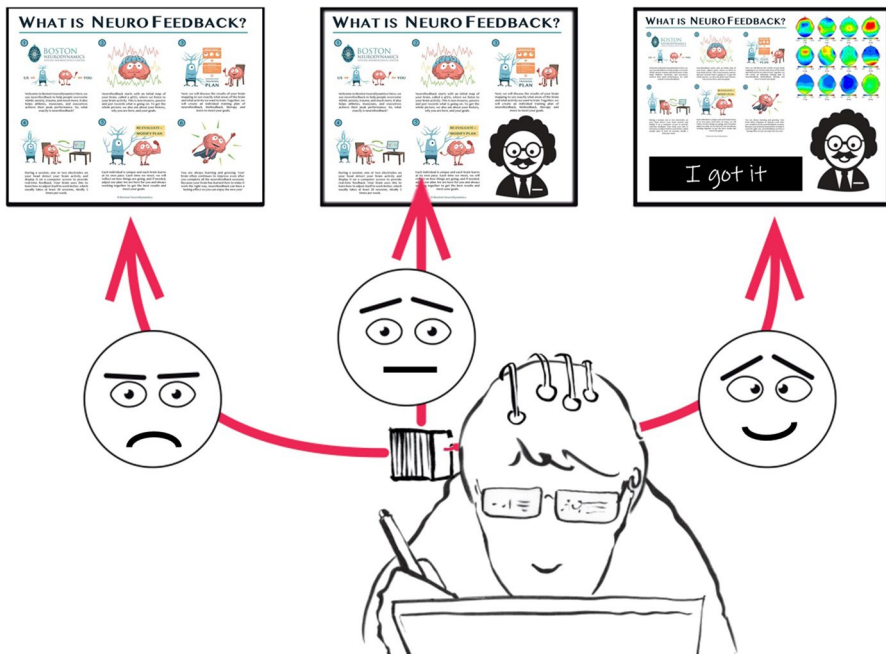


Fig. 1 Neurofeedback-based educational BCI system. BCIs can properly monitor the student's mental state by measuring brain activity. Using this information and signals for cognitive load, frustration level, or exhaustion, the teacher tailors its teaching technique to the student's mental state to help the student in the learning process

3 Methodology

3.1 Search strategy

Following the guidelines for Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Liberati et al., 2009), this SLR was conducted on four well-known literature digital databases (Fig. 2): IEEEExplore, Scopus, PubMed, and ScienceDirect. IEEEExplore is a robust tool for finding and access to scientific and technical material. Furthermore, Scopus provide more coverage compare to Web of

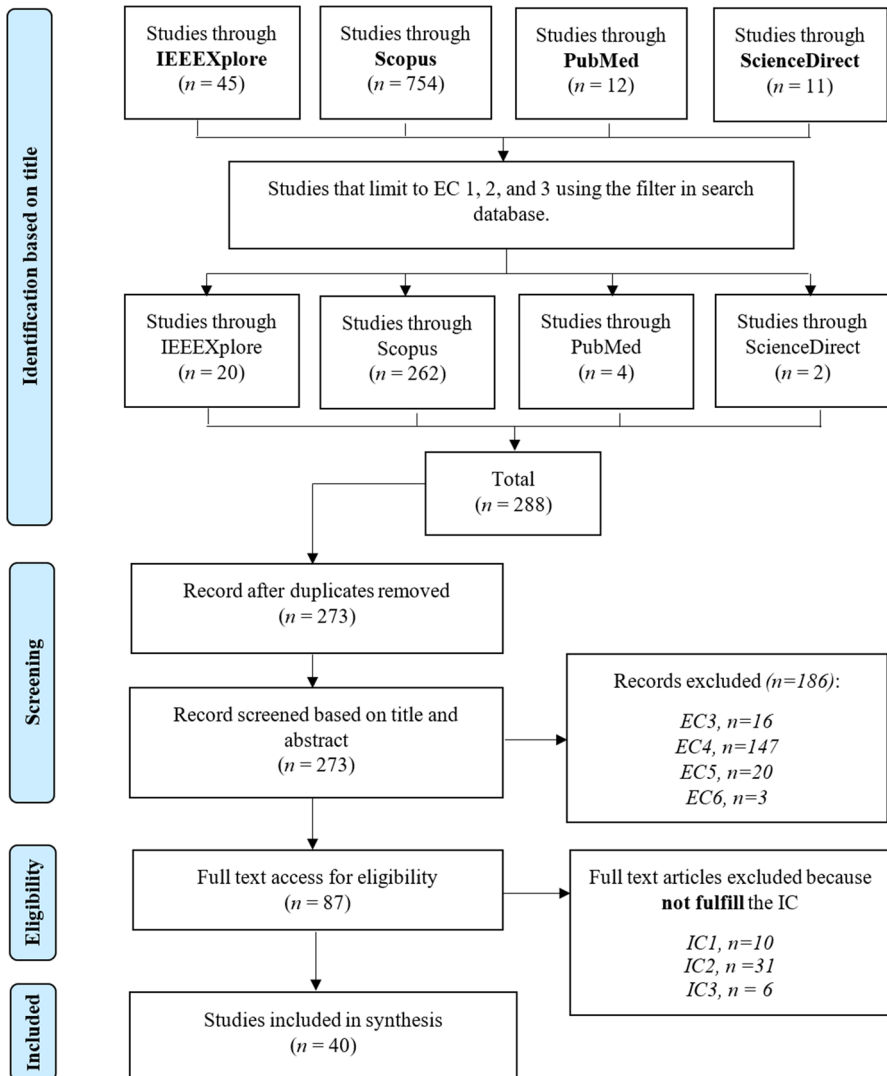


Fig. 2 Flow chart of the PRISMA survey method

Science (Bar-Ilan, 2018). While PubMed focuses more on medical and health which BCI is commonly used in the medical sector and ScienceDirect obtain to a huge scientific and medical research database. The search was carried out from early March 2022 to the end of April 2022, and covered three years of publishing (2020-2022) to capture the recent research trends regarding Covid-19 and education, with a special focus on abruptly transitioning of face-to-face classroom teaching to online teaching methods for remote learning beginning in early 2020

The specific keyword strings used for each database in this SLR are given in full detail below:

- **IEEE**: (((“Document Title”:eeg OR “Document Title”:electroencephalo* OR “Document Title”:eye tracking) AND (“Document Title”: student* OR “Document Title”: teacher*) AND (“Document Title”: online learn* OR “Document Title”: remote learn* OR “Document Title”: distance learn* OR “Document Title”: e-learn*)) OR ((“Abstract”:eeg OR “Abstract”:electroencephalo* OR “Abstract”:eye tracking) AND (“Abstract”: student* OR “Abstract”: teacher*) AND (“Abstract”: online learn*OR “Abstract”: remote learn* OR “Abstract”: distance learn* OR “Abstract”: e-learn*))
- **Scopus** : TITLE-ABS(eeg OR electroencephalo* OR “eye tracking”) AND (student* OR teacher*) AND (“online learning” OR “remote learning” OR “distance learning”)
- **PubMed** : ((eeg[Abstract] OR electroencephalogram[Abstract] OR “eye tracking”[Abstract]) AND (student[Abstract] OR teacher [Abstract]) AND (“online learning”[Abstract] OR “remote learning”[Abstract] OR “distance learning”[Abstract] OR “e-learning”[Abstract])) AND ((eeg[Title] OR electroencephalogram[Title] OR “eye tracking” [Title]) AND (student[Title] OR teacher[Title]) AND (“online learning”[Title] OR “remote learning”[Title] OR “distance learning”[Title] OR “e-learning”[Title])))
- **ScienceDirect** : (eeg OR electroencephalogram OR eye tracking) AND (student OR teacher) AND (online learning OR remote learning OR distance learning)

3.2 Inclusion and exclusion criteria

These criteria as identifiers used to determine which subject and focus will be included in this SLR. A study was included in this SLR based on the following inclusion criteria (IC):

- **IC1**: The healthy participants either students, teachers or both
- **IC2**: The work was a primary study that reported measures of student/teacher performance in a learning environment that included at least one of online learning, e-learning, blended learning, or remote learning
- **IC3**: The methods used included EEG or eye-tracking

and a study was excluded using the following exclusion criteria (EC):

- **EC1:** The publication year was earlier than 2020.
- **EC2:** The study was not a pre-reviewed paper or was a review/survey paper and/or a book chapter
- **EC3:** The publication was in a language other than English
- **EC4:** The education environment studied was not related to an online method, such as online learning, blended learning, virtual learning, or remote learning
- **EC5:** Studied focused on virtual reality as a tool
- **EC6:** The article was not retrievable fully

3.3 Content Analysis

The full-text article was obtained with the assistance of a librarian for each study that matched the inclusion criteria. Data were extracted with four areas of focus: 1) influence factors associated with cognitive skills as influence factors (such as attention, learning behavior, and emotion) can affect the learning process; 2) the tools and techniques used to measure cognitive skills; 3) the experimental tasks to see the diversity of task being used during the experiment; and 4) the implementation of feedback or neurofeedback as it is important to enhance and improve student learning. The extracted data from selected papers use a statistical method (meta-analyses) to integrate and summarize the data for the results. These analyses can show a statistically combined result of many different tools to measure the student's cognitive abilities and the most influential factor that affects the cognitive skills.

4 Findings

We reviewed numerous studies and retrieved 288 articles, but after screening using the qualifying criteria, only 40 articles were included. Because certain databases did not provide particular study type filters, EC3 was employed once again (Fig. 2). In addition, some reviews and survey papers were mislabeled as a type of journal article. This section summarizes the review's results and discusses them in separate subsections in responses to each of the research questions.

4.1 RQ1:How to measure the cognitive abilities of students in the remote learning environment?

Figure 3 compares the fraction of five methods among all studies reviewed that measured the cognitive skills of students in the online learning environment and relied on using a standalone device such as EEG, eye-tracking, or dual devices. Eye-tracking was the most frequently employed device, accounting for nearly two-thirds of the total articles. The second most frequent method used, at 30%, was EEG. Hybrid methods, combining EEG and eye-tracking, eye-tracking and head pose, or eye-tracking and heart rate, each accounting for a mere 2.5% of all articles reviewed. One benefit of the use of the hybrid method is that it can discriminate students' behavior during online classes.

Fig. 3 Doughnut chart showing the fraction of published articles categorized by the methods used to measure the influence factor

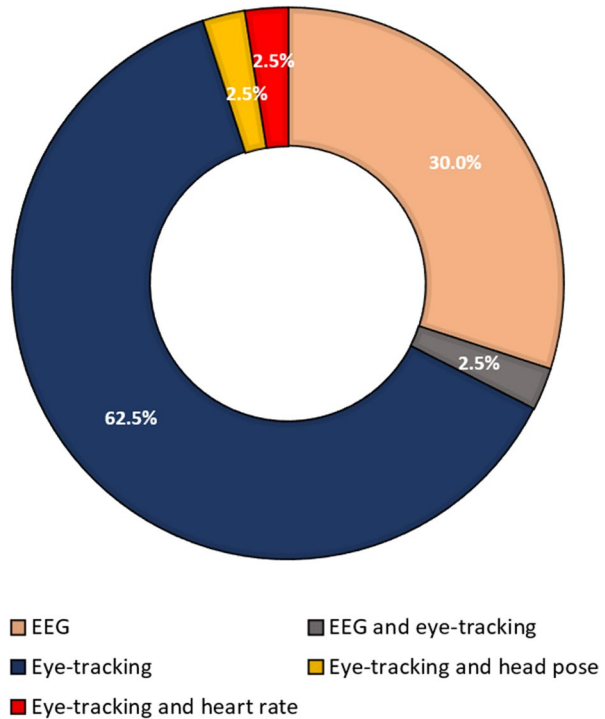


Figure 4 was created using the metadata from the publications included in the SLR. Of 339 keywords, the most occurrences keywords are eye tracking with 19 times occurrences, followed by e-learning 15 times and students 13 times. The spelling for the keyword reflects the occurrences. For instance, the keywords “eye tracking” and “eye-tracking” were counted as different. 54 keywords appear at least 2 times and 285 keywords only appear once in published articles.

Figure 5 summarizes the methods employed in the reviewed articles and the influence factors that they were used to measure. Again, eye-tracking leads with 25 articles (Brandenburger et al., 2019; Srivastava et al., 2021; Nugrahaningsih et al., 2021; Hocine, 2021; Wang et al., 2020; Dilini, 2021; Matthew, 2021; Wang et al., 2020; Kokoç et al., 2020; Sharma et al., 2020; Liu et al., 2022; Lee and Muldner, 2020; Pi et al., 2020; Polat, 2020; de Mooij et al., 2020; Yang et al., 2021; Zhai et al., 2022; Jónsdóttir et al., 2021; Anggraini et al., 2020; Hachisuka et al., 2021; Chen et al., 2021; Rets & Rogaten, 2021; VandenPlas et al., 2021; Zhang, 2021; Shojaee et al., 2021) This is not surprising as that device has become widely available and capable of giving researchers unparalleled access to user’ attention. Of these articles, five measured more than one influence factor, including attention and learner perception (Wang et al., 2020), attention and emotion (Liu et al., 2022), attention and motivation (Sharma et al., 2020), and attention and learning performance (Chen et al., 2021; VandenPlas et al., 2021).

	EEG	EEG & Eye-tracking	Eye-tracking	Eye-tracking & head pose	Eye-tracking & heart rate
Attention	7	×	14	×	1
Behaviour	×	×	1	×	×
Cognitive load	3	1	3	×	×
Concentration	×	×	×	1	×
Emotion	1	×	1	×	×
Engagement	×	×	1	×	×
Learning performance	1	×	7	×	×
Learning style	×	×	1	×	×
Learner perception	×	×	1	×	×
Motivation	×	×	1	×	×

Fig. 5 Devices and the influence factors of education they were used to measure in online learning

of the three papers, Alrawahneh & Safei (2021) used eye-tracking combined with a head pose detection method to measure the students' concentration while watching a lecture video in an e-learning class. Feedback on students' concentration would be sent to the teacher's computer so the teacher could adjust the educational technique and material style for students. In third paper, Francisti et al. (2020) used smartwatches and eye-tracking technologies, devices that are widely available. They used data from these gadgets to study how the students' attention affected their performance.

The NeuroIS community believed that the public collection of biosignals and the subsequent analysis using supervised machine learning, it is feasible to identify cognitive load (Vanneste et al., 2021). It takes a significant quantity of data to train a classifier to the level of accuracy needed. However, the dataset from the retrieved articles are mostly directly recruited, and only one article uses the public dataset repository. Furthermore, some of the retrieved articles did not publish the type of machine learning classifier. These articles directly showed the statistical analysis of the data. Tables 1, 2 and 3 show the visible dataset and classifiers for articles based on measurement devices EEG, eye-tracking and hybrid methods, respectively.

These three tables (Tables 1, 2 and 3) show some of the articles do not mention the name of the classifier, considering the purpose of the papers not to classify the brain's wave or eye-tracking movement. The articles did not evaluate machine learning performance. Therefore, the papers focus more on the result by using statistical analysis such as ANOVA or t-test. Given the papers using statistical analysis, comparing before and after the experiment to see the improvement of students' cognition is more significant for the studies.

Table 1 Overview of dataset (number of participants) and classifiers for articles based on EEG

Article	Dataset	Classifier	Statistical Analysis
Aggarwal et al. (2021)	12 students	Support Vector Machine	–
Hsu (2021)	67 students	Not mentioned	t-test
Gupta and Kumar (2021)	80 students	Classification algorithm	–
Tikadar & Bhattacharya (2021)	15 students	Support Vector Machine	–
Udayana et al. (2021)	20 students	Deep learning	–
Pi et al. (2021)	26 students	Not mentioned	ANOVA
Umezawa et al. (2020)	18 students	NeuroSky device algorithm	Chi-squared test
Conrad and Newman (2021)	48 students	Not mentioned	Linear mixed model
Baharum et al. (2020)	10 students	Not mentioned	–
Ni et al. (2020)	28 students	Chip's algorithm (Mind wave)	–
Jitsopitanon et al. (2021)	27 students	Not mentioned	t-test
Lin et al. (2022)	38 students	Not mentioned	ANOVA

4.2 RQ2: How can students improve their learning in the remote learning environment?

Giving relevant feedback to students may considerably improve their learning and performance. Effective feedback encourages students to reflect on their learning and learning practices and make changes to enhance their learning process (Torres et al., 2020; Boase-Jelinek et al., 2013). However, based on the articles included in this SLR, only six out of forty (15%) articles provided feedback or neurofeedback (Fig. 6).

Three of the six articles implement neurofeedback by using EEG devices. Gupta and Kumar (2021) provided neurofeedback about students' engagement and predicted that the attention of students who did not feel engaged with the subject or content would decrease. The second of the three papers, by Udayana et al. (2021) reported on the improvement of the student's attention level supervised independently by the student during the breathing exercise. In the third paper, Baharum et al. (2020) used the Effective Learner application to monitor the students' focus level. The application came with a display of color-coded indicators of six focus levels.

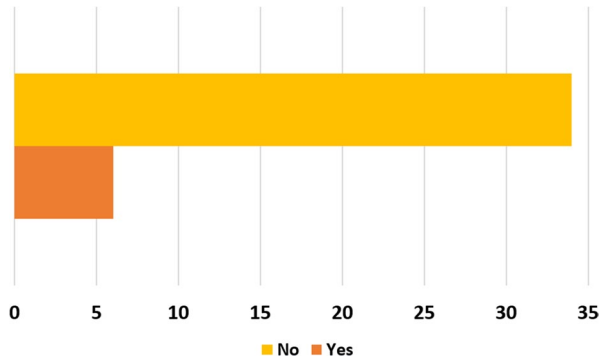
Wang et al. (2020) built a program that could gain immediate access to the streaming from a webcam for real-time eye-tracking and forecasting of the students' level of engagement on four pre-defined levels: (i) not engaged, (ii) less engaged, (iii) engaged, and (iv) high engaged. In another study, Alrawahneh & Safei (2021) were observing students during a task and provided direct feedback to the teacher about their concentration level relative to those of experts. Finally, Hachisuka et al. (2021) proposed a method in which students had to verbally answer quizzes. For feedback, the proper answer and explanation for each question were presented with details provided by the teacher. This learning system was shown to instill a sense of security in students while seeing the teacher's face and maintain their concentration.

Table 2 Overview of dataset (number of participants) and classifiers for articles based on eye-tracking

Article	Dataset	Classifier	Statistical Analysis
Brandenburger et al. (2019)	20 students	Not mentioned	t-test
Srivastava et al. (2021)	45 students	Not mentioned	Discrete Time Markov Chain
Nugrahaningsih et al. (2021)	90 students	Not mentioned	Shapiro-Wilk test
Hocine (2021)	40 students	Convolutional Neural Network	–
Wang et al. (2020)	dataset DAiSEE	Convolutional Neural Network	–
Dilini (2021)	10 students	One-Class Support Vector Machines	–
Matthew (2021)	23 students	Not mentioned	Linear mixed model
Wang et al. (2020)	60 students	Not mentioned	ANOVA
Kokoç et al. (2020)	116 students	Not mentioned	ANOVA
Sharma et al. (2020)	40 students	Support Vector Machine & Random Forest	Gaussian distribution
Liu et al. (2022)	60 students	Not mentioned	t-test & Mann-Whitney U test
Lee and Muldner (2020)	77 students	Not mentioned	Null Hypothesis Significance Testing , Bayesian & ANOVA
Pi et al. (2020)	174 students	Not mentioned	ANOVA
Polat (2020)	64 students	Not mentioned	ANOVA & Mann-Whitney U test
de Mooij et al. (2020)	39 students	Not mentioned	t-test & ANCOVA
Yang et al. (2021)	63 students	Not mentioned	ANOVA
Zhai et al. (2022)	48 students	Not mentioned	t-test
Jónsdóttir et al. (2021)	40 students	Not mentioned	ANOVA & Linear regression equation
Anggraini et al. (2020)	30 students	Not mentioned	Multivariate analysis
Hachisuka et al. (2021)	6 students	Not mentioned	The average gaze time percentage
Chen et al. (2021)	40 students	Not mentioned	ANOVA & t-test
Rets & Rogaten (2021)	37 students	Not mentioned	ANOVA
VandenPlas et al. (2021)	16 students	Not mentioned	ANOVA
Zhang (2021)	28 students	Not mentioned	ANOVA
Shojaee et al. (2021)	201 students	Not mentioned	ANOVA

Table 3 Overview of dataset (number of participants) and classifiers for articles based on hybrid methods

Article	Dataset	Classifier	Statistical Analysis
Alrawahneh & Safei (2021)	10 students	Haar Cascade	–
Francisti et al. (2020)	Sample of students	Nearest squares' (clustering)	Lilliefors test
Liu (2021)	42 students	Not mentioned	Mann-Whitney U test & ANOVA

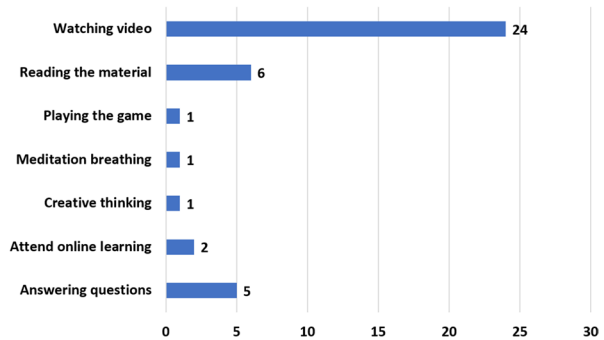
Fig. 6 Feedback or neuro-feedback applied in empirical research

4.3 RQ3:How to evaluate the student interaction in the absence of student-teacher eye contact?

This section reviews recent research on brain-to-brain synchronization under student-teacher interaction. As shown in Fig. 5, none of the articles included in this SLR measured student-teacher brain synchronization in the remote learning environment. As discussed earlier, interaction is one of the most important influence factors of learning, characterized by mutual acceptance, comprehension, affection, closeness, trust, respect, caring, and collaboration (Duchesne & McMaugh, 2018). The formation of a positive student-teacher interaction, according to developmental theory, helps a student's cognitive, social, and emotional development and improves their mental health (Brazelton & Greenspan, 2000).

Figure 7 shows the distribution of the 40 studies in this survey according to seven kinds of tasks, including (i) answering questions, (ii) attending online learning, (iii) creative thinking, (iv) meditation breathing, (v) playing the game, (vi) reading learning material and (vii) watching video. Watching video was the overwhelmingly preferable tasks, with 24 articles (Alrawahneh & Safei, 2021; Aggarwal et al., 2021; Brandenburger et al., 2019; Srivastava et al., 2021; Gupta and Kumar, 2021; Hocine, 2021; Tikadar & Bhattacharya, 2021; Matthew, 2021; Tsai et al., 2012; Kokoç et al., 2020; Sharma et al., 2020; Liu et al., 2022; Liu, 2021; Lee and Muldner, 2020; Pi

Fig. 7 Distribution of the research papers surveyed by the task they studied



et al., 2020; Polat, 2020; Pi et al., 2021; Conrad and Newman, 2021; Yang et al., 2021; Anggraini et al., 2020; Chen et al., 2021; VandenPlas et al., 2021; Lin et al., 2022; Zhang, 2021) using it in the experiments. Reading and answering questions were a distant second and third, with six (Chen et al., 2017; Umezawa et al., 2020; Ni et al., 2020; Zhai et al., 2022; Jónsdóttir et al., 2021; Rets & Rogaten, 2021) and five articles (Francisti et al., 2020; Dilini, 2021; Baharum et al., 2020; de Mooij et al., 2020; Hachisuka et al., 2021), respectively. Although three articles (Wang et al., 2020; Pi et al., 2020; Anggraini et al., 2020) had the teacher being present in the video, there was still no opportunity for real-time interaction between students and the teacher because the video was pre-recorded. These experiments were more designed to gauge the effect of the teacher’s presence in online learning. None of the articles measured the brain-to-brain synchronization between student and teacher, even though this approach would measure the students’ engagement. This notion is supported by at least one study, reporting that students who self-reported being more interested in class had brain waves more in sync with their teachers (van Atteveldt et al., 2020). Table 4 summarizes the 40 publications included in our survey.

5 Discussion

We performed a systematic literature review (SLR) of current methods of measuring the cognitive skills of students during online learning and highlighted several key influence factors and tasks that are preferable for this measuring. Of the 40 studies reviewed here, about half used EEG or eye-tracking with a focus on attention as an influencing factor. This shows the a sustained interest in this influence factor. However, attention is worth investigating in combination of additional influence factors, such as student interaction, for their achievement and satisfaction. As has been well documented, students’ mental health became a major public health problem during Covid-19. This crisis was shown to be associated with the separation between students and instructors, the difficulty of utilizing online platforms, the absence of advice and counseling, and the high levels of distractions present in online platforms. The inability to communicate and interact with lecturers has shown to be the major source of stress for students (Akpınar et al., 2021).

Table 4 The retrieved papers on students' cognitive abilities in online learning

Article	Purpose	Method	Task	Feedback/ Neurofeed- back
Aggarwal et al. (2021)	To evaluate attention level of undergraduate students during MOOC/e-learning environment	EEG	Watching recorded video	X
Hsu (2021)	Get the information about tourism students' cognitive load and learning outcome based on face-to-face and online learning	EEG	Face-to face & Attend online learning	X
Gupta and Kumar (2021)	To monitor and improve the attention levels of students	EEG	Watching recorded video	✓
Tikadar & Bhattacharya (2021)	Proposed a model to detect affective state of student during e-learning environment	EEG	Watching recorded video	X
Udayana et al. (2021)	To explore the breathing exercise based on yoga (Dasa Aksara Pranayama) for improve the focus on distance learning	EEG	Meditation breathing	✓
Pi et al. (2021)	To tested the effectiveness of three learning strategies (self explanation, learning by teaching and passive viewing) by watching the video lecture	EEG	Watching recorded video	X
Umezawa et al. (2020)	Propose a system and a method for estimating the learning state of the students by comprehensively analyzing the learning history	EEG	Reading the material	X
Conrad and Newman (2021)	To explore the relationship between watching the video lecture with mind wandering	EEG	Watching recorded video	X
Baharum et al. (2020)	To develop mobile-application for flipped classroom	EEG	Answering the questions	✓
Ni et al. (2020)	To analyzed the student's attention in three different type of learning media (text, text+graphic, video) using mobile device	EEG	Reading the material	X
Jitsopitanon et al. (2021)	To examine the constructivist web-based learning can enhance student's creativity thinking	EEG	Creative thinking	X

Table 4 (continued)

Article	Purpose	Method	Task	Feedback/ Neurofeed- back
Lin et al. (2022)	To investigate the relationship between attention and academic achievement	EEG	Watching recorded video	X
Brandenburger et al. (2019)	To investigate the different visualization during online learning based on students' preferable	Eye-tracking	Watching recorded video	X
Shrivastava et al. (2021)	To measure the attention while students watching the video as learning material	Eye-tracking	Watching recorded video	X
Nigrahaningsih et al. (2021)	To distinguish the between visual and verbal learning style based on gaze during e-learning	Eye-tracking	Answering questions	X
Hocine (2021)	Proposed the MOOC gamification (trophies, avatar and progression bar) for student attention	Eye-tracking	Watching recorded video	X
Wang et al. (2020)	To evaluate and monitor the student engagement during online learning	Eye-tracking	Attend online learning	✓
Dilimi (2021)	To detect the cheating student during online examination	Eye-tracking	Answering questions	X
Matthew (2021)	To investigate how the subtitle can influenced in as recorded and subtitle lecture	Eye-tracking	Watching recorded video	X
Wang et al. (2020)	To investigate how the instructor influence learning and learner's perception	Eye-tracking	Watching recorded video	X
Kokoç et al. (2020)	To explore the different types of video lecture (voice over type, picture-in-picture type, and screencast type) can effect the student attention in e-learning environment	Eye-tracking	Watching recorded video	X
Sharma et al. (2020)	To investigate the stimuli based-gaze can enhance motivation and learning in MOOC environment	Eye-tracking	Watching recorded video	X
Liu et al. (2022)	To explore how the different level of reflection can effect the learning outcome	Eye-tracking	Watching recorded video	X

Table 4 (continued)

Article	Purpose	Method	Task	Feedback/ Neurofeed- back
Lee and Muldner (2020)	To investigate the impact of instruction video style (monologue with instructor presence, dialogue with instructor presence and video without instructor presence)	Eye-tracking	Watching recorded video	X
Pi et al. (2020)	To investigate the eye-gaze and body orientation factors in the video lecture can influence the students' attention	Eye-tracking	Watching recorded video	X
Polat (2020)	To investigate the effect of text-positions (right side and bottom) presented at two videos	Eye-tracking	Watching recorded video	X
de Mooij et al. (2020)	To investigate either learning environment impact the cognitive load on math performance	Eye-tracking	Answering questions	X
Yang et al. (2021)	To tested the motivation relationship between pre-interpolated questions and learning from video lectures	Eye-tracking	Watching recorded video	X
Zhai et al. (2022)	To investigate the stimulated recall in remote learning environment	Eye-tracking	Answering questions	X
Jónsdóttir et al. (2021)	To investigate the effect of language and time pressure on English as first language (EFL) and second language (ESL)	Eye-tracking	Reading the material	X
Angraini et al. (2020)	To investigate the effect of tutor-presence in learning video	Eye-tracking	Watching recorded video	X
Hachisuka et al. (2021)	To clarify the effect of the teacher's facial image during online learning	Eye-tracking	Answering questions	✓
Chen et al. (2021)	To compare two layout of video with comments can affect the student's attention	Eye-tracking	Watching recorded video	X
Reis & Rogaten (2021)	To explore the text simplification on English second language students	Eye-tracking	Reading the material	X

Table 4 (continued)

Article	Purpose	Method	Task	Feedback/ Neurofeed- back
VandenPlas et al. (2021)	To determine how screen-case and simulations can support students understanding	Eye-tracking	Answering questions	X
Zhang (2021)	To investigate the effect of video subtitle on learning performance	Eye-tracking	Watching recorded video	X
Shojaee et al. (2021)	To explore how eye-tracking metric can relate with students' attention	Eye-tracking	Playing the game	X
Liu (2021)	Investigate the effectiveness of color coding in video lecture about programming	EEG Eye-tracking	Watching recorded video	X
Arawahneh & Safei (2021)	Measure student's concentration level during e-learning environment	Eye-tracking Head pose	Watching recorded video	✓
Francisti et al. (2020)	To find the connections between the individual Internet of Things (IoT) devices and students' concentration	Eye-tracking Heart rate	Answering the questions	X

The survey indicates that most of the selected articles did not provide feedback or neurofeedback to students. Neurofeedback can be used to teach the brain to self-regulate and assist the student in identifying their desired brain condition. Steiner et al. (2014) proved that neurofeedback is more effective than cognitive-behavioral therapy and suitable for attention training. Attention training will increase one's ability to maintain concentration on a task. Strained students may sustain their attention for a longer period before becoming fatigued. With neurofeedback, the student may become aware when their attention sags (Gupta and Kumar, 2021) and teachers can monitor the student engagement during the online class (Wang et al., 2020). This feedback system will enable teachers to understand the students better and offer the most effective methods to improve learning or develop more appropriate material or subject content.

The experiment tasks in the reviewed studies mostly focused on students watching a pre-recorded video. Among the benefit of using the recorded material in online education, the student can access and view the content as many times as they need it to get a better understanding. Nonetheless, the recorded video has the limitation of explanation and examples. When the student doesn't understand the content from the given examples, they are not offered further explanation; they are confined to listening and watching the same examples repeatedly. This is in contrast with watching a real-time video in which the student has the opportunity to communicate and interact directly with the teacher. When students are given a chance to engage synchronously through videoconferencing, their performance has been found to improve marginally (Skylar, 2009). The real-time video benefits both students and teachers because they want to communicate, comprehend, and be understood.

To overcome the above issues, we propose the following solutions:

- Implement a new experimental paradigm with hybrid methods (e.g., EEG and eye-tracking devices) that focus on remote learning
- Explore neurofeedback using a BCI and eye-tracking approach to collect factual data.
- Investigate whether remote interaction affects brain-to-brain synchronization between student-teacher.

A new experimental paradigm can be planned by using a non-invasive technique to measure the brain activity and eye movement of healthy students (in higher education) in a remote learning environment. The student will spend roughly ten to fifteen minutes attending the course with the real-time (not pre-recorded) video in which they have the opportunity to interact directly with the teacher (Fig. 8). Because we want to capture their behavior in their natural environment, students are encouraged to move around, take notes, and engage with their belonging.

A previous study has demonstrated brain-to-brain synchronization in the face-to-face class setting (Bevilacqua et al., 2019) and indicated that students who had more social interaction with the teacher revealed brain-to-brain synchronization, which specifically refers to the anatomical similarity of the active brain regions during social contact. This result suggests that it would be useful to investigate brain-to-brain synchronization during remote learning. We would want to know whether even in the absence of eye-gaze or face-to-face interaction, the students and the

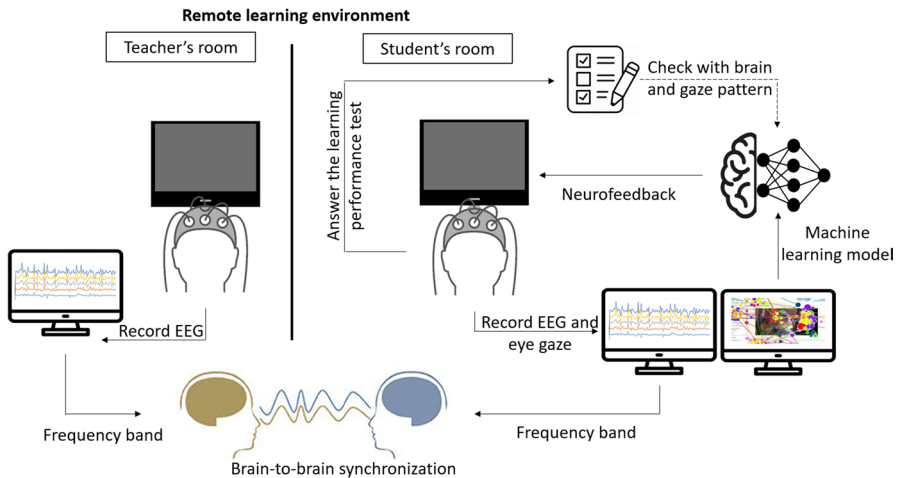


Fig. 8 A hypothetical experimental paradigm for a class held in a remote learning environment. Each student and the teacher would sit in a different room, using online tools, such as Microsoft Team or Learning Management System. The student interacting with the teacher would be wearing an EEG and eye-tracking equipment, while the teacher would be wearing only the EEG equipment. Later, their brain-waves would be analyzed off-line for brain-to-brain synchronization

teacher still maintain the same understanding of the content being explained and can increase student engagement with the topic.

The history of online learning is long and varied (various types of online learning, such as blended learning, distance learning, and Massive Open Online Courses (MOOCs)). It wasn't until the mid- 20th century that online learning took off (Harasim, 2000). The development of computers and the internet made it possible for people to access courses from anywhere in the world (Kentnor, 2015). Online learning became increasingly popular in the late 20th century for several reasons. First, it was much cheaper than traditional education; second, it allowed students to get quality education from anywhere in the world; and finally, it allowed students to learn at their own pace, without having to miss class or take long breaks.

Online learning has been around for a long time, but it wasn't until the outbreak of Covid 19 that it became popular. Before covid 19, online learning was mainly used by students who needed to take courses that were too difficult or time-consuming to attend in person. With covid 19, online learning became a viable option for students to continue the education, syllabus, and learning process. Since COVID-19 is no longer an issue, online learning will attract a new crowd. In addition, the emergent flexibility and educational opportunities will likely transform the standards of both students and teachers, further blurring the distinction between traditional classroom instruction and online education (Jonassen et al., 2008).

To establish techniques and paradigms of pedagogy that will be most effective for remote learning, we focused on the associations between cognitive science and teaching practice under remote teaching conditions. Throughout remote learning education, we concentrate on establishing remote learning through the development of interaction, communication, and cooperation between the teacher and students.

6 Limitation

This SLR may have several shortcomings that affect its overall quality. First, it's possible that potential studies will be affected since the search for studies might have also included data from other digital databases. On the other hand, we chose the most comprehensive digital databases covering the SLR subject. It's possible that using other libraries only led to additional instances of duplicates being created. Furthermore, the quality of the data obtained from the included articles was directly proportional to the quality of the analysis.

Second, limitations include the inclusion criteria for this SLR that focuses on healthy participants only. Nevertheless, there should be some variety in the participant scales, such as participants with autism or anxiety. They have a different level of acceptance of knowledge compared to normal and healthy participants, and the influencing factor may also differ.

Additionally, the articles included in this SLR focus on BCI and eye-tracking only. Future studies are recommended to consider virtual reality because that opens up a lot of possibilities for simulating both the actual world and the imaginative world. It can be an extra advantage to create an imaginary online environment.

7 Conclusion

Due to the Covid-19 pandemic, remote learning is here to stay and will certainly continue to expand and impact higher education. This SLR examined the EEG and eye-tracking devices currently in use for monitoring and measuring the various influence factors in remote learning environment. Different tasks were used in the experiments to measure influence factors. We grouped them into seven categories. The development of additional BCI and eye-tracking applications for remote learning to measure students' cognitive skills promises to guide restructuring of online education with a positive outcome.

While remote learning education is strongly embedded in the planning and design of instructional materials using various possible models and theories, the transitioning to the online platform has been questioned due to the lack of proper preparation, design, and development of online instructional programs. Additionally, teachers need to conform to new pedagogical ideas and a more flexible delivery method. Students' may suffer emotionally due to the new conditions in the educational environment under Covid-19.

Neuroeducation might be utilized as a foundation, particularly for teachers, to understand the student's brain better and assist future academic performance in any situation. Furthermore, micro-credentials allow teachers to complete demanding and self-directed projects related to the communication skills required in the classroom. This new wave of professional learning paradigm provides teachers with a means of getting recognition for their talents through formal and informal learning opportunities and customizing and applying their professional training with students during the teaching-learning process.

Finally, this SLR points to new directions for future research, especially in a remote learning environment. In future studies, we intend to explore the pedagogical techniques with the ability to lead and improve teaching and learning for the newly adapted norms, and we aim to continue to expand research in education.

Author Contributions AB conceived the topic and conducted the conceptual design for the review. NJ conducted the literature survey and wrote a preliminary version of the manuscript. AB, NJ, AL contributed to selecting the articles and analyzing the results. All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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Data availability Data generated from the digital library; IEEE, PubMed, Scopus, and ScienceDirect at United Arab Emirates University and available upon request.

Declarations

Conflicts of interest The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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