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# Cognitive and Affective Brain–Computer Interfaces for Improving Learning Strategies and Enhancing Student Capabilities: A Systematic Literature Review

NURAINI JAMIL<sup>1</sup>, ABDELKADER NASREDDINE BELKACEM<sup>2</sup>, (Senior Member, IEEE),  
SOFIA OUHBI<sup>1</sup>, AND CHRISTOPH GUGER<sup>3</sup>, (Member, IEEE)

<sup>1</sup>Department of Computer Science and Software Engineering, College of Information Technology, UAE University, Al Ain, United Arab Emirates

<sup>2</sup>Department of Computer and Network Engineering, College of Information Technology, UAE University, Al Ain, United Arab Emirates

<sup>3</sup>g.tec medical engineering GmbH, 4521 Schiedlberg, Austria

Corresponding author: Abdelkader Nasreddine Belkacem (belkacem@uaeu.ac.ae)

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**ABSTRACT** Brain–computer interface (BCI) technology has the potential to positively contribute to the educational learning environment, which faces many challenges and shortcomings. Cognitive and affective BCIs can offer a deep understanding of brain mechanisms, which may improve learning strategies and increase brain-based skills. They can offer a better empirical foundation for teaching–learning methodologies, including adjusting learning content based on brain workload, measuring student interest of a topic, or even helping students focus on specific tasks. The latest findings from emerging BCI technology, neuroscience, cognitive sciences, and psychology could be used in learning and teaching strategies to improve student abilities in education. This study investigates and analyzes the research on BCI patterns and its implementation for enhancing cognitive capabilities of students. The results showed that there is insufficient literature on BCI that addresses students with disabilities in the learning process. Further, our analysis revealed a bias toward the significance of cognitive process factors compared with other influential factors, such as the learning environment and emotions that influence learning. Finally, we concluded that BCI technology could improve students’ learning and cognitive skills—when consistently associated with the different pedagogical teaching–learning strategies—for better academic achievement.

**INDEX TERMS** 21st century abilities, applications in subject areas, brain computer interface, improving classroom teaching, neurofeedback, teaching/learning strategies.

## I. INTRODUCTION

Learning is the cognitive process of acquiring knowledge, values, and skills through formal or informal education and instruction. It is one of the most effective brain processes that not only helps people develop economically, socially, and intellectually but also allows one to obtain careers that help sustain a certain quality of life. The process of learning starts in early childhood and is a continuous, lifelong process because the brain is constantly growing and changing in real-time as it adapts to new information and circumstances. Formal education is considered to have specific

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impacts on the development of skills, talents, potential, and knowledge [1]. One fundamental purpose of education is providing students with the skills relate to problem-solving, logical and creative thinking, and succeeding in life. Measuring such awareness and skills is essential for monitoring the growth of students and their educational performance. Educators use various measurements throughout the learning process, including student achievement in particular subjects [2], working memory capacity [3], attention [4], and cognitive skills [5].

Several factors, such as students’ mental health and motivation, influence formal learning. For instance, mental health disorders or even simple stress may hinder the cognitive learning process. An ill-adjusted child finds it impossible

to focus [6], which requires mental wellbeing and a lack of mental tension or difficulty. Some students face difficulties studying for examinations solely because of various anxiety and panic paranoia [7]. There is broad scientific evidence that a relaxed and healthy mind can reduce stress and negative effects on learning [8], [9]. However, a lack of motivation will hamper productivity and result in dissatisfaction and annoyance [10]. In the absence of inspiration, a student may not be motivated to learn. Students' involvement in learning is triggered by desires, chosen by interest, and guided by actions. Incentives could play an essential role in motivating students in the learning process [11].

Presently, sensor technologies increasingly offer new approaches in education. Promising research has been produced on brain-computer interface (BCI), and it is starting to be used in other domains, such as education. The control of a computer by thoughts using invasive or non-invasive brain measurements is primarily used in clinical applications—for example, the engagement and communication between paralyzed patients and the outside world. In recent years, growing numbers of consumer goods and applications, which focus not only on individuals who are disabled but also on education to measure stress and concentration, have been introduced [12]. The brain activity can be invasively or non-invasively measured and tested with different brain waves, such as alpha, beta, and theta waves with various BCI frequencies. These different waves can reflect the mental states of a person [13]–[15]. Attaching the sensor at the prefrontal lobe helps collect information to best interpret the workings of the mind and determine actions or behavior, as the prefrontal lobe is hugely relevant and related to the human abilities of thinking and cognition [16]. The research shows that when the relationship among brain cells is amended, there can be a positive change in the transition in brain cells that improve human functions [17]. Using BCI as cognitive tools, the human brain can be investigated to analyze, understand, and improve the learning process. In this paper, we focus on cognitive and affective BCIs that reveal neural information about the affective (e.g., emotions and moods) and cognitive (e.g., learning and memory) states of a student and that the interaction between students and teachers can be aided by recognizing those user states. This paper conducts a systematic literature review (SLR) to answer the following research questions (RQs):

- **RQ1.** What are the key influencing factors for enhanced learning in education using BCI technology?
- **RQ2.** What are the participants exposed to in cognitive and affective BCIs to measure the influencing factors in the field of education and what directions have neuroscientists and neuroeducation researchers pursued to assess the effectiveness of BCI applications in improving learning strategies and enhancing cognitive capabilities?

This SLR aims to identify the different types of participants and the experimental task procedures used to measure the learning influence components reported in literature.

We retrieved over 3,000 articles and, after a careful review process, selected 186 to include in this SLR.

### A. THE USE OF NEUROTECHNOLOGIES AND NEUROSCIENCE

Brain computer interface (BCI) is an emerging multidisciplinary technology in which the brain and devices are directly connected using some electrodes or sensors to measure the brain activity [18], [19]. BCI uses integrated hardware and software based on various neuroimaging techniques to either directly or indirectly record brain activity or image the structure, function, or pharmacology of the nervous system to understand the human brain and responds with actions or commands to control an external devices or communicate with environment. To build such a BCI system for neurological and cognitive-psychology research, there are some common requirements typically appear in this order: data acquisition, feature extraction, classification, or decoding, and send the commands and receiving feedback from the BCI-based device control. These requirements require everything from selecting relevant brain signals to recording them reliably by using either of two methods, invasive or non-invasive, to analyzing the user brain activity in real-time for adaptive interactions between the user and the BCI system. Closed-loop BCI is mainly based on Neurofeedback concept (neurotherapy) which is a kind of biofeedback that teaches self-control of brain functions to BCI users by measuring brain waves and providing a feedback signal in order to reinforce healthy brain function through operant conditioning (i.e., associative learning process).

While engaged in cognitive activity, the brain's neurons generate electrical pulses that synchronize to generate brainwaves. Four brainwaves are alpha, beta, theta, and delta. Beta waves are generated whenever the brain is engaged in mental activity with the highest amplitude, the frequency range of 15 to 40 hertz, and are the fastest. During non-arousal states, the Alpha waves can be seen. A person who has finished a task and has relaxed for a while is typically in an "alpha" state. These oscillate at a frequency of 9 to 14 cycles per second. Theta waves are around 5-8 Hz in amplitude and slightly slower. While daydreaming, an individual is frequently in a theta state. The biggest waves are called delta waves, and they're the slowest, which between 1.5 and 4 Hz and represent a dead brain.

All these brainwaves can be captured during signal acquisition. The invasive method is a process of decoding brain signals by going directly into the cerebral cortex. The surgical implantation of an electrode or sensor into the skull is required to receive the best signals [20]. Non-invasive is the most popular means of acquiring the EEG signal by placing electrodes on a person's scalp. This method delivers good signal quality at a low price and is simple to use. Nevertheless, when compared to an EEG signal obtained through invasive means, the acquired signal is noisy. [21].

BCI systems allow users to send messages and commands from the mind to a computer through direct electronic signals,

without any movement [22]. BCI can allow persons with physical disabilities to perform several actions that enhance their wellbeing and quality of life by allowing data transmission between the subject and computers [23]. BCI can allow a person with physical disabilities to regain abilities, such as hand movements, and enhance functions, such as grasping or walking [24].

The majority of BCI devices were designed to aid physically challenged users in regaining movement ability and compensating for lost or reduced motor functionality [25], [26]. Despite that, BCI applications not just applicable in the medical area [27]. Various other fields are making innovative use of the developments in this technology in multiple ways. Some researchers using BCI applications in-home appliances to control some devices by using the signal from the brain such as lights, fans, and cleaning robot [28]–[30]. BCI applications are also beneficial for the elderly for enhancing their quality of life [31]. Elderly people can use the exoskeleton and a wheelchair to support their motor control impairments [32], [33]. In the entertainment area, EEG signals can be used to monitor the players' performance, such as the time to complete the task and the point for achieving the objectives of the games [34]. Furthermore, the BCI applications have been implemented in other areas including in education. BCIs may be learning tools for students and educational instruments for instructors. A BCI may assess and monitor a learner's cognitive states, gather the relevant information, and then alter the training procedure to meet the specific learning demands of that student [35]. Moreover, students can improve their enthusiasm in the learning process [36].

Therefore, this paper focuses on non-invasive BCI using EEG signals in the education area. Understanding the brain is the crucial factor for successful learning. Focus on how the appropriate support for education may lead to a good development of mind and brain.

## B. EDUCATION AND LEARNING

The United Nations Educational, Scientific and Cultural Organization has identified education as one of the world's highest priorities [37]. A well-balanced education can provide a vision of the future and allow people to create goals and a life philosophy. Furthermore, education develops literacy, critical thinking, and imagination skills as well as many cognitive skills, such as thinking, reasoning, and attention to detail.

An instructor's philosophy may influence what subjects or topics are taught, how they are taught, and the principles and values that support the curriculum. The teacher transfers knowledge to students and is also required to display respect for authority, commitment, a work ethic, compassion, and sensitivity toward students. Teachers and schools thrive when students use what they have learned to achieve success. Learning outcomes are usually measured by assessments developed with two philosophies in mind, namely, (i) essentiality and (ii) consistency [38]. Other philosophies that

educators should know about are student-centered philosophies. Students learn actively and relate to what they learn based on how and when it is learned. Students are therefore actively involved in the learning process as well as responsible for their learning. Students and teachers strive together to decide what to learn and how to learn effectively. School should never be viewed as a student-controlled institution or one that encourages the preservation and dissemination of the dominant culture but as an institution that works with students to strengthen society and support them to achieve their best individual potential [39].

Learning theories are essential to explaining various aspects of the learning process, which can be clustered into three main domains, namely, (i) cognitivism, (ii) behaviorism, and (iii) constructivism. Cognitivism focuses on the brain and cognitive process to deal with information, such as through understanding, remembering, and solving learning problems [40]. In behaviorism, learning occurs by incentives and penalties that contribute to behavioral improvements [41]; students will be more motivated if they receive more rewards. Constructivism is based on observation, in which students build their understanding through experiences and by reflecting on knowledge [40]. Teachers typically allow students to use active strategies—such as real-world problem-solving and experiments—to generate better insight and develop analytical skills.

Conversely, education, knowledge, and experience significantly influence the cognitive development of the human brain, thereby creating a bridge between neuroscience and education (neuroeducation). Knowledge of changes in the human brain could enhance teachers' understanding of the student's mind [42], including the attention, cognition, and difficulties related to education. Previously, students or children who found it difficult to grasp standard school subjects were considered as having learning disabilities, such as dyscalculia [43] and dyslexia [44]. Therefore, not only should learning strategies between ordinary students and students with disabilities be different but also the assessments and tests [45].

One common situation that teachers face is students not paying attention or not concentrating on the learning process for the duration of the class. Some students get distracted, doze off, or do other things. Some teachers can handle such situations by making their classes more engaging. Several researchers investigated students' attention, concentration, and engagement during the learning process. Reigel *et al.* [46] examined the relationship between simplicity and complicated response times in primary education for children with selective attention. The duration of a student's attention during the lecture in class was analyzed by visual attention, especially for children with Attention Deficit Hyperactivity Disorder (ADHD) because they had sustained attention [47], [48]. Student-based performance was used to measure the engagement between students during collaborative work [49], and student engagement in two countries was compared based on teaching–learning strategies [50].

Feedback from the student's understanding can help teacher to change their teaching style for increase students' motivation and attention in the class [51].

In contrast, teachers play a vital role in helping students gain more knowledge and be educated. Therefore, a teacher's behavior, quality of teaching, or even strategies used to transfer knowledge can contribute to effective learning. There have been several studies that have investigated how students' achievement can be bolstered by the teacher [52]–[55], and there is a broad interest in showing that teaching quality can provide better learning for students [56]–[58]. Therefore, mental effort in the classroom and the relationship between students and teachers influence the learning process.

In 2002, the Organization for Economic Co-operation and Development reported the risk about misconceptions in neuroscience (called neuromyths) that can affect education and learning processes. Neuro-myths are a misconception or misquote of scientifically proven facts that can become evidence for using research about the human brain in education [59]. For instance, a teacher might tell a student that they have a visual style of learning and then provide teaching aids that primarily rely on images. The student may internalize that they are a visual learner, which may influence the learning process for years ahead. However, it is possible to preclude the development of the student by limiting the learning styles; thus, the visual learner student might no longer have the potential to enhance their hearing ability. In education, the interplay between a student's motivation and teacher expectations in academic performance remain to be fully grasped [60]. Moreover, teachers who believe in neuro-myths can also search for more about brain information. Therefore, BCI can be an effective tool to overcome the effects of the misconception about neuro-myths and to teach students according to their needs.

Learning styles as a concept of each students have different style to accept the mode of instruction in learning process. Many models of learning style were created such as David Kolb's model in 1984, Peter Honey and Alan Mumford's model in 1984 and Neil Fleming's model in 1987. However, there is no real scientific evidence that people can be classified into discrete groups based on their learning styles (e.g., Visual, Kinesthetic/tactile, Auditory) [61], [62]. In addition, these researches have not found any evidence in supporting the use of learning-style evaluation [63]. Despite the lack of evidence supporting the use of learning styles, many school teachers still believe in this controversial theory. Therefore, learning styles can be a good example of neuromyths.

In this review, we consider learning styles as a keyword for influence factors in the search methodology, and then we carefully and critically discuss the weakness of papers who have been published claiming that learning styles-biological and developmental characteristics may have some scientific evidence in affecting how we learn.

### C. COGNITIVE AND AFFECTIVE BRAIN-COMPUTER INTERFACES IN EDUCATION

Presently, many applications based on neuroscientific evidence are utilized by cognitive- and affective-related multi-disciplinary disciplines. Cognitive process can be measured by memory, workload, attention and language while the affective process more on emotion and motivation. Therefore, BCI can be a tools to analyze the brain signal, including neuro-feedback, and improve cognitive activity to restore learning and memory [64]. For instance, people's affective or cognitive states can be measured using the BCI to determine the cognitive load and avoid mental fatigue.

BCIs are useful for measuring cognitive processes, which means that there is a greater opportunity for the training to be adapted based on the learner's current condition, which should enable a better education of the user. Example in learning mathematics using abacus, the BCI system can detect the brain activity during the calculation process and see the different signals and brain changes between the expert and novices students [65]. Therefore, with these information, the educator can improved adaption of content and different way of teaching to maximize the student's performance in learning. Furthermore, in affective process, the BCI can help to reduce the anxiety. The majority of students that struggle with mathematics are always concerned during the process of completing mathematical problem. BCI devices can record real-time brain activity and offer visual feedback to the student as anxiety levels rise, attempting to assist the student in regaining control [66].

Moreover, BCI technologies have proven useful for restoring, enhancing, improving, supplementing, and replacing the motor and cognitive abilities, which lead to empowering directly or indirectly. The teacher and learners perform many tasks most productively and indirectly impact the learning outcomes due to improvements in concentration, mood, emotion, and cognitive abilities of BCI users. Example, the BCI application can be used in cognitive behaviour intervention directly such as social cognitive skills training for Autistic Spectrum Disorder (ASD) people. BCI application empower participants by providing immediate feedback on their attention focus. This information enables the individual to self-monitor their performance about where to gaze and, thus, enables them to change their behavior [67]. At the same time, BCI devices that stimulate the brain neuroplasticity, which may result in the restoration of motor function [68]. For example, with BCI training, the stroke patients showed the improvement in opening hand movement of the paretic hand using exoskeleton [69]. So, indirectly BCI application can become one of the alternatives to help students which paralyzed or have motor impairment to continue the learning process.

In correlation, BCI affect and contribute in learning process. Teachers must consider the students' cognitive development and understand their need to promote better learning while designing and developing the learning

environment. Therefore, neurofeedback is an appealing approach to improve cognitive function by modulating human brain activity to evaluate the degree of clarification regarding the information learned [70].

Therefore, BCI becomes a promising tool in many fields, including education, for understanding and measuring brain activity. Some projects have been developed using BCI devices. Further, current education models and support systems have been established to enhance the learning method and strengthen cognitive abilities of healthy people as well as persons with disabilities. Along with recent advances in education and the potential associated with BCI, researchers have begun to attend to serious questions on how BCI can help the students' learning abilities.

BCI has been used in experiments designed to create knowledge for educational theorists and practitioners [71]. Some education research used mobile electroencephalogram (EEG) headbands to study brain activity within the classroom setting [72], [73]. BCI can apply to understanding the brain and inspecting the development of a student's mental state. Other methods of research can examine potential behavioral mechanisms that influence the brain and student cognition. Simultaneously, neuroimaging studies have investigated and assessed brainwaves to identify discrepancies concerning selective attention [74]–[76]. For measuring and interpreting brainwaves, understanding the activity of the brain is significant. The brain function's electromagnetic patterns can be detected using non-invasive tools like EEG. In an EEG, which is the most common method for measuring, electric brain signals produced by brain activities are monitored and documented using sensors [77]–[79]. Further, cells in the brain will align with each other and generate the electrical signal whose activity patterns can be analyzed.

Moreover, BCI can offer information through several motor controls and complex cognitive features for measuring people's memory [80], attention [81], concentration [82], cognitive skills [83], and learning style [84]. Measuring attention, cognitive skills, emotion, and other factors that influence student learning provide many advantages for monitoring the student's performance in academic subjects. Furthermore, the BCI framework for assessing mental concentration, attention, and cognitive levels is useful in neuropsychology and education, especially for children or students who have attention disorders, such as ADHD [85], learning disabilities [86], or anxiety [66].

Numerous studies using EEGs have consistently found that the measurement and evaluation for the learning process of student mental states are a combination of the alpha and theta wave frequency [87]–[89]. The activity in the theta wave was reported as being favorably correlatable, with the preference for memory as well as a predictive factor of changes in cognitive tasks, specifically in the frontal lobe. A strong correlation between the neuronal spiking observed that the more significant theta oscillation coordinates can combine the different mental functions of a cognitive task [90], [91]. [90] research showed improved amplitude and synchronization in

various frequencies of cognitive tasks and oscillatory activities, particularly in theta (4–7 Hz) and alpha (8–13Hz). EEG is also used for educational purposes for understanding student mental status by examine and observe students' brain activity [92].

BCI-based supporting factors, such as learning style, lifestyle, and mental wellbeing, can contribute to the learning progress and affect education performance [93]–[95]. Psycho-education has become particularly relevant in recent years in which the students and families are provided with reliable information on mental health or specific symptoms of depression or stress [96]. For example, it has been established that insufficient sleep is associated with attention deficiency, decline in academic performance, depression, and poor health conditions. Students may also have inadequate information regarding sleep disorders and sleep health habits, thus contributing to bad sleep hygiene [97], [98]. Figure 1 illustrates the relationship between cognitive and affective BCIs and education.

## II. METHODOLOGY

### A. RESEARCH QUESTIONS

This SLR focuses on applying neuroimaging, psychoeducational, and cognitive methods to investigate the interplay among students, teachers, and their learning environment in shaping the learning process and the development of cognitive and affective skills. The RQs of this SLR, with their rationale, are shown in Table 1.

### B. SEARCH STRATEGY

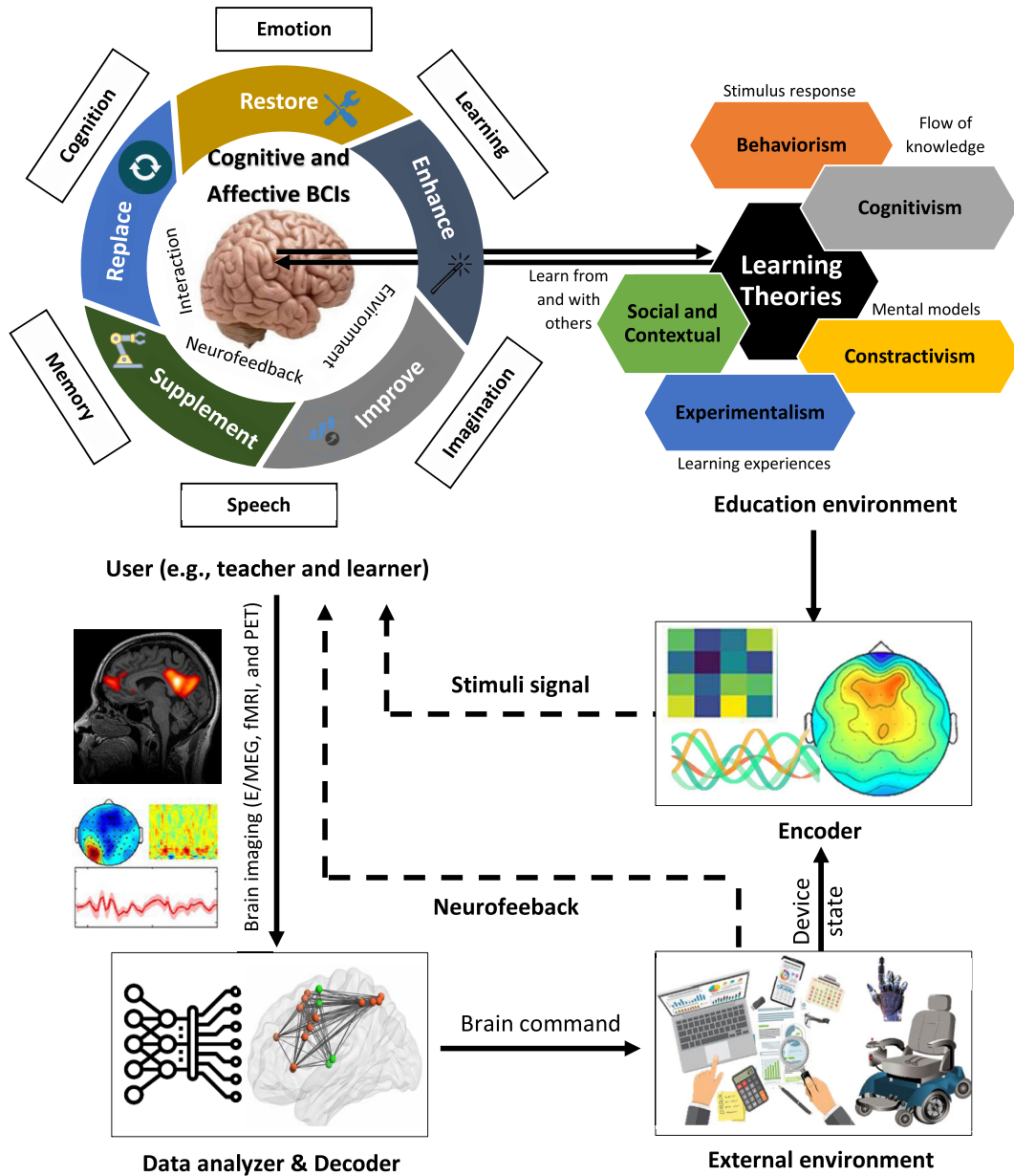
This SLR followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses recommendation [100]. An online search was conducted in the following digital databases: IEEEXplore, Scopus, PubMed, and ScienceDirect. The search was performed between July 2020 and early December 2020, covering 10 years of publication (2011–2020), to capture the most recently used BCI technology in education and the see the future direction in BCI ([http://bnci-horizon-2020.eu/images/bncih2020/FBNCI\\_Roadmap.pdf](http://bnci-horizon-2020.eu/images/bncih2020/FBNCI_Roadmap.pdf)). The search also limited the title of the document to reduce the search result.

The primary search string used to search for relevant literature was the following: (BCI or “brain–computer interface” or EEG or electroencephalo\*) and (educat\* or attention or student or learn\* or concentrat\* or “cognitive activity.”)

The search string was adjusted for each specific database. After screening the title, we excluded duplicated publications. The titles and abstracts of all listed literature were screened to identify relevant studies. We retrieved and screened the full text of all relevant articles using inclusion criteria to determine the article's validity as being significant by using the cross checked method between the authors.

### C. SELECTION CRITERIA

Studies were included in this systematic review if they met the following inclusion criteria(IC): (IC1) studies in which participants are students or children (normal (i.e, healthy) or



**FIGURE 1.** Relationship between BCI and education. BCI extracts the most relevant brain features for cognitive–affective states to measure the influencing factor based on the learning theories. Cognitive and affective BCI will help to understand how critical factors such as empathy, creativity, self-control, and problem solving develop and how these can influence the learning process. In the same time, numerous changeable environmental variables, such as education, mental illness, and disease, can all have an effect on an individual’s intelligence quotient (IQ). [99].

**TABLE 1.** Research Questions.

No.	Research Question	Rationale
1.	What are the key influencing factors for enhanced learning in education using BCI technology?	To evaluate the effectiveness of using BCI to assess students’ mental state and the influencing factors that best enhance the learning process and achieve better performance in education.
2.	What are the participants exposed to in cognitive and affective BCIs to measure the influencing factors in the field of education and what directions have neuroscientists and neuroeducation researchers pursued to assess the effectiveness of BCI applications in improving learning strategies and enhancing cognitive capabilities?	To investigate and compare the trend of participants’ attention and ways to extract more information to better reflect the diversity of students at different level of education.

with disabilities) because educational needs are different at different ages [101], children with these disabilities such as

dyslexia or attention deficit hyperactivity disorder (ADHD) struggle with learning and that affects their brain functions,

particularly paying attention and memory [102]; (IC2) teacher as a support system for the student in education; and (IC3) the influencing factors that can enhance learning in education. The primary influences chosen for this review were attention and concentration, measured by BCI. However, no limitation was set on the component that can influence learning, such as learning style, stress, emotion, and the learning environment.

The exclusion criteria (EC) for this review were as follows: (EC1) published before 2011; (EC2) publications that were neither peer-reviewed or were review; (EC3) non-English articles; (EC4) studies that recruited subjects unrelated to education; and (EC5) studies that were indirectly related to education or were out of the scope of the component that can enhance learning. Figure 2 illustrates the stages of the selection process.

#### D. DATA EXTRACTION

With the help from a librarian, a full-text article was retrieved for each study that met the inclusion criteria. We extracted the characteristics of the selected articles, including the type of participants, component for enhancing the learning, and participants' task or method to measure the enhancing factors. We categorized the influencing factors that can enhance learning into the following four major groups:

- The cognitive process factor, which is related to processes that affect cognition, including attention, concentration, confusion, memory, engagement in cognitive activity or skills, and motor skills.
- The individual and behavioral factor, which is how student learns, including learning style, performance and learning level, sleep, self-efficacy, and learning behavior.
- The affective/emotional factor, which involves feelings that can affect outcomes, including motivation, emotion, and stress.
- The learning-environment factor, which is the condition and place of the learning process.

### III. RESULTS

A total of 186 articles out of 3,460 candidate studies were selected in this SLR. EC 1, 2, and 3 were automatically applied during the string search in the digital database. Unfortunately, some of the publication titles did not mention review papers, and the ScienceDirect database does not provide language filtering. Therefore, some of articles were manually excluded (EC 2 and 3) during the eligibility stage (see Figure 2).

#### A. RQ1: WHAT ARE THE KEY INFLUENCING FACTORS FOR ENHANCED LEARNING IN EDUCATION USING BCI TECHNOLOGY?

Figure 3 presents the mapping between influencing factors and participants identified in the selected studies. Participants have been classified into the following two categories:

- Normal, which includes healthy children (age > 11 years old), school students (age between 11 to

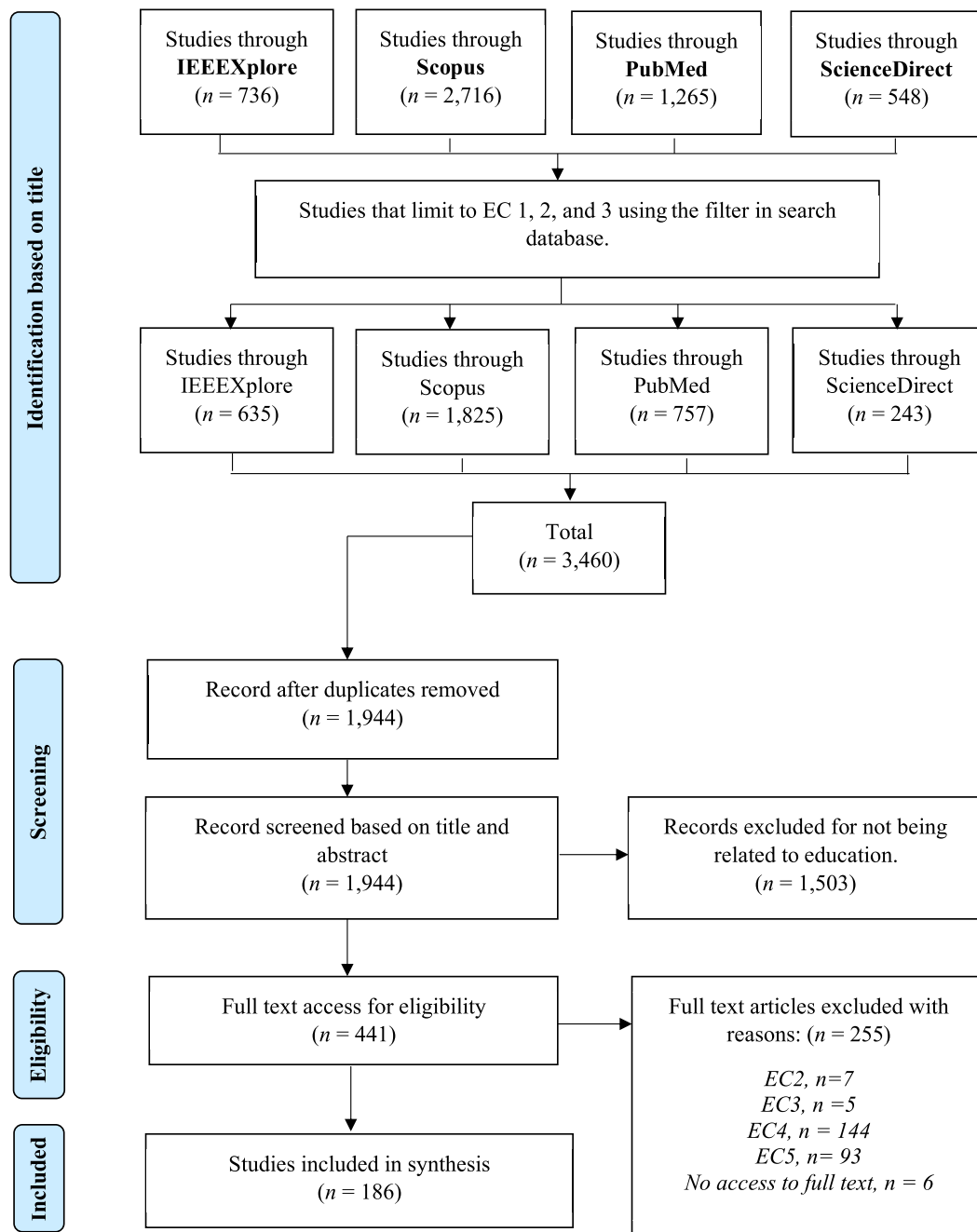
17 years old), university or college students (age < 17 years old), and teachers or educators.

- Disabled, which refers to participants with conditions such as dyslexia, autism, learning disability, ADHD, diabetes or internet addiction.

Table 3 shows the studies for normal and disabled participants, whereas Table 4 shows the studies as per influencing factors.

#### 1) COGNITIVE PROCESS FACTORS

- 1) Attention: This is the most persistent influencing factor for the learning process, as identified by 31.2% of the total articles (n = 58). Around 79.3% (n = 46) of these articles within this category discussed normal participants, whereas 20.7% (n = 12) of the articles in this category were about the disabled group. Only one article discussed both normal and disabled children as participants. Most studies for the normal group focused on university or college students (55.2%, n = 32). The remaining 15.5% (n = 9) of selected studies explain about cognitive process factors for students, and 8.6% of articles (n = 5) were related to children. The disabled group articles were overwhelmingly about children (17.2% of articles, n = 10); only 1 article each was about disabled university or college students and school student.
- 2) Concentration: We classified 8.6% (n = 16) of total publications for the normal group as addressing concentration, with the majority using university or college students as participants within this category (75%, n = 12). School students were the topic of 18.8% of publications (n = 3) about concentration, with one article on children. There was only one paper on university or college students in the disabled group.
- 3) Confusion: Only 1.6% of total articles (n = 3) on confusion were about the normal group. In total, 67% of the articles (n = 2), within this category used university or college students as participants, and one article addressed school students.
- 4) Memory: In total, 9.1% of the publications (n = 17) were classified to this influencing factor. University or college students were the topic of 70.6% of these articles (n = 12) within this category, and only two articles were about school students and one article was about children, belonging to a normal cluster. In contrast, only one article discussed children as participants for both normal and disabled groups and remaining article discussed about children in disabled group.
- 5) Engagement and focus: We classified 4.3% of the total articles (n = 8) as belonging to both categories of participants. Only one article targeted disabled children, with 63% of these articles (n = 5) being about normal university or college students. One article each explained about normal school students and children.
- 6) Cognitive activity/skills and motor skills: This is the second most influential factor in this review,



Note: EC– Exclusion Criteria, PRISMA-Preferred Reporting Items for Systematic Reviews and Meta-Analyses, n– number of publications

FIGURE 2. Flow Diagram Using PRISMA phases.

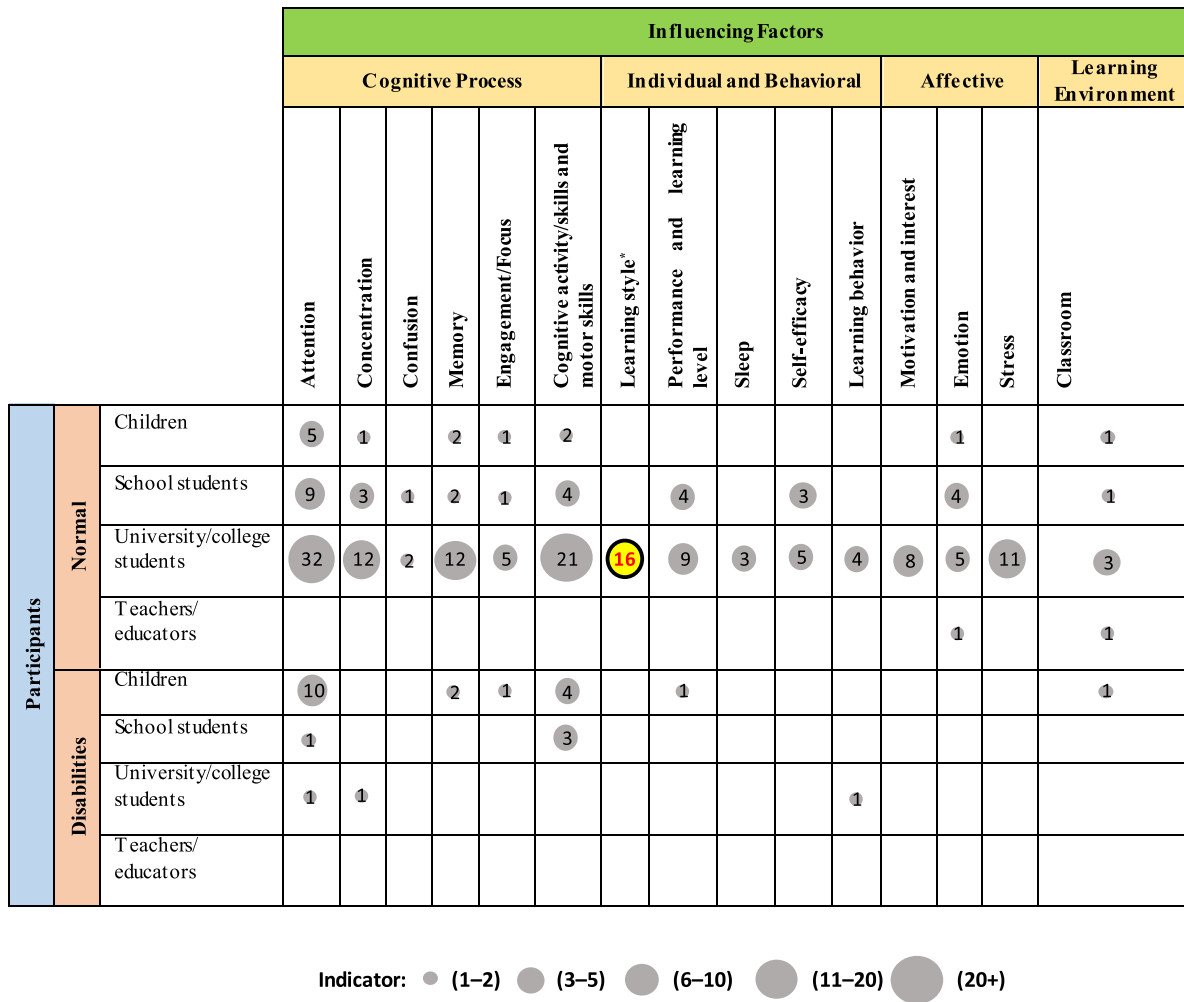
with 18.3% total articles (n = 34), of which 79% (n = 27) were about normal participants and 21% of studies (n = 7) about disabled participants. Around 62% of the articles (n = 21) within this category covered university or college students as participants. School students and children were the subject of 12% (n = 4) and 6% (n = 2) of articles, respectively. Only one article was related to motor skills for children with ADHD to see whether exercise can develop the

executive function in the brain. The other 18% of the articles (n = 7) within this category addressed the disabled group, with 12% of the articles (n = 4) being about children and 9% (n = 3) about school students.

## 2) INDIVIDUAL AND BEHAVIORAL FACTORS

1) Learning style: Surprisingly, we found that learning styles are the most considered influence on the





Note: Disabilities participants have one of the following disorders: dyslexia, learning disability, autism, internet addiction, diabetes or attention deficit hyperactivity disorder. \*denotes a neuromyth. However, some researchers claimed that they found some EEG evidences to prove the learning style as one of influencing factor in learning process. Their number of publication papers about learning style is highlighted in red and yellow.

**FIGURE 3. Mapping between participants and influencing factors identified in the selected articles. The size of each circle displays the proportion of reviewed studies as shown in indicator. The left columns show the participants with two main groups, normal and disabled. The top row shows the four main clusters for influence factor in learning especially in education.**

individual and on behavioral factors in education with 8.6% of the total publications (n = 16). All publications were classified into the normal category about university and college students.

- 2) Performance and learning level: This is the second most popular influential factor in this category, with 8% of the total articles (n = 14). The article division was 67% (n = 9) about university or college students and 27% (n = 4) about school students. We only found one publication regarding disabled children because of dyslexia.
- 3) Sleep: Sleep was mentioned in 1.6% of the total publications (n = 3), all focusing on the university or college students as participants.
- 4) Self-efficacy: We classified 4.3% of the total articles (n = 8) in the normal category. Three articles were

about school students, and the other 63% of the articles (n = 5) within this category covered university and college students.

- 5) Learning behavior: We classified 2.7% (n = 5) of total articles into this category. A total of 80% of the articles (n = 4) within this category examined normal university or college students, while one publication covered normal and disabled university or college students.

### 3) AFFECTIVE FACTOR

- 1) Motivation and interest: We classified 4.3% of the total articles (n = 8) into this influence factor. The participants were mainly university and college students.
- 2) Emotion: The normal category encompassed 5.9% of the total articles (n = 11). The most frequent cluster was about university or college students with 45% of

the articles ( $n = 5$ ) within this category, followed by school students with 36% of the articles ( $n = 4$ ). One publication was about children and one article about educators in universities.

- 3) Stress: normal participants from university and college, which was the only category covered in this factor, were discussed in 5.9% of the total articles ( $n = 11$ ).

#### 4) LEARNING-ENVIRONMENT FACTOR

- 1) We classified 3.2% of the total articles ( $n = 6$ ) in the normal category. School students and teacher interaction in the classroom were addressed in the same article as brain-to-brain studies, and there was one other article that had university or college students for identifying an effect of learning with music in the background. Only one article was discussed about children in disabled category.

Table 2 provides one example of publication for each influencing factor based on the included articles. Each influencing factor has been ranked independently. The main criteria for the examples are as follows: (i) participants, (ii) publication type, and (iii) purpose (how the measurement is conducted). Children have to evolve in academic, social, and emotional ways during formal education in school [103]; however, children can also shape their education, social skills, and emotional skills to succeed or fail based on adapting to the changing contexts of formal learning [104]. Moreover, a BCI helps to identify the influences on these changes as well as to treat students, such as those with ADHD, to increase their attention or any other influencing factors in learning [105]. The second criterion based on the reputation of the journal. The ranking can represent the journal with a high impact [106]. The last criterion to be included is purpose because there is a need to see effectiveness of measurement that can reflect the outcome.

#### ***B. RQ2: WHAT ARE THE PARTICIPANTS EXPOSED TO IN COGNITIVE AND AFFECTIVE BCIs TO MEASURE THE INFLUENCING FACTORS IN THE FIELD OF EDUCATION AND WHAT DIRECTIONS HAVE NEUROSCIENTISTS AND NEUROEDUCATION RESEARCHERS PURSUED TO ASSESS THE EFFECTIVENESS OF BCI APPLICATIONS IN IMPROVING LEARNING STRATEGIES AND ENHANCING COGNITIVE CAPABILITIES?***

Figure 4 illustrates the number of articles published per year from 2011 to 2020. Our review shows that 21.4% of the studies were published in 2020, which is the highest percentage. At the beginning of the period, in 2011, only 3 articles were published, and in 2012, only 4 articles related to BCI and education were published. Over the next 5 years, the level fluctuated, with a difference of not more than 10 articles. Nevertheless, there was apparent statistical growth in the number of publications from 2011 to 2018. The year 2018 shows the publication's most dramatic development, climbing from 18 in 2017 to 39 publications

in 2018. The New Media Consortium reported that emerging technology trends were needed to focus on measuring the learning, especially for higher education [121]. There was a slight decrease in the number of publications in 2019—36 publications—while in 2020, 40 publications were retrieved as of early December 2020. We used extrapolation function to predict the number of total articles for the year 2020 and 2021. We have used a polynomial extrapolation with order 3. However, these data cannot be accurately predicted, especially for the years 2020 and 2021 in the educational setting because of challenging time cause by Covid-19, (<https://www.iesalc.unesco.org/en/2020/03/09/coronavirus-covid-19-and-higher-education-impact-and-recommendations>).

Figure 4 also show the trend per participant type, namely, children, school students, university or college students, and teachers. University and college students consistently contribute to the studies for BCI and education, with the number increasing from 2012, which is expected to be even higher in 2020. Only in 2019 did teachers participate in the studies. The previous years, all the participants were children and students. Surveys of teachers emphasized the stress and poor mental health of teachers (American Federation of Teachers, [https://www.aft.org/sites/default/files/2017\\_eqwl\\_survey\\_web.pdf](https://www.aft.org/sites/default/files/2017_eqwl_survey_web.pdf)); therefore, teacher data are highly needed to solidify the positive relationship between teachers and students for learning processes. The data suggest the number of children has fluctuated since the early years.

In this paper, one-way repeated-measures ANOVA followed by Scheffé's multi-comparison test were conducted. We used a one-way ANOVA to find out whether different publication classes of an independent variable have different effects on the publication year. Significant differences ( $F(3,36) = 9.86, P < 0.001$ ) were observed between the four classes (see Figure 5).

#### **IV. DISCUSSION**

The results of this SLR showed that many BCI studies focus only on university or college students. This finding is not surprising considering many of the conducted experiments were at university laboratory spaces where it is relatively easy to get student volunteers. Nevertheless, the participant scales should be varied because different levels of education will offer different strategies in learning [101]. The children in primary schools have a different level of knowledge acceptance than school and university students, and the influencing factor might also be different. For instance, in the early stage, children might not need to focus on critical thinking to solve problems. The situation is different from higher education, wherein the students need to think critically to achieve the learning objective [122]. In particular, we found few BCI studies based on normal children's perspectives [109], [118], [123]–[125]. BCI can be a treatment tool for students with disabilities who have ADHD, autism, or any other related condition that can decrease the ability of learning [126]. Incorporating the BCI method in education has proven to be

TABLE 2. Potential articles sorted by learning influence factor.

Influencing factor	Author	Participants	Purpose	Task	Outcomes
Attention	Lim et al. [105]	20 children (16 boys and 4 girls) with ADHD. Age 6–12	To investigate if the individual learns to increase attention while playing a game.	-Using 3D graphic game and Cogol and to control an avatar using EEG. -EEG was measured during Stroop task.	-Inattentive and hyperactive impulsive symptoms showed improvement on ADHD rating scale. -BCI ADHD measures correlated with ADHD rating scale.
Concentration	Zhang [107]	19 college students (10 males and 9 females) with slight dyslexia. Average age (22.7)	Develops a web-based Non Feedback (NFB) training system that is applied at college to enhance English learning.	-Have training on English spelling and reading. -The assessment involves memory recall and memory recognition, Stroop color-word interference test, and attention-switching test.	-NFB training showed enhancement in English learning in web applications.
Confusion	Lin and Kao [108]	32 health university students (16 male and 16 female). Age 22–30	To classify if students felt confused about the video content based on e-learning (MOOC).	-Participants need to press button “k” at the red sticker if they do not understand something while watching the video. -Participants need to answer 3–5 questions after watching the video.	-The classification for learners’ learning states showed high rates for accuracy, precision, and recall. -Accessed self-awareness about the mental state during online learning.
Memory	Fernández et al. [109].	18 children with LD (14 boys and 4 girls) Mean age 9.4  16 normal children (8 boys and 8 girls) Mean age 9.2	To examine the EEG oscillations between normal and LD children based on unrelated pairs of words (attention and working memory).	-The children need to right- or left-click the mouse based on the second word depending on whether it is related with the first word by using Spanish words.	-Results showed physiological differences between the normal and LD group that affect the cognitive performance. -LD showed smaller number of correct responses.
Engagement/ focus	Hillard et al. [110].	18 children and adolescents with ADHD (12 boys and 6 girls) Mean age 13.6	To enhance the focus and alertness by watching documentary series.	-Participants need to watch the video until 25 minutes for each session for 12 sessions.	-Positive effects of improvement in focus based on neurofeedback using audiovisual selective attention test and aberrant behavior checklist were observed.

**TABLE 2. (Continued.) Potential articles sorted by learning influence factor.**

Cognitive activity/skills and motor skills	Vollebregt et al. [111].	41 children with ADHD. Ages 8–15	To evaluate whether F-NF had beneficial effects on neurocognitive functioning in children with ADHD.	-The participants need to watch the movie within 20 minutes. -Before and after testing, participants need to take the neurocognitive test.	-Result failed to show support of neurofeedback on neurocognitive function for ADHD.
Learning style*	Jawed et al. [112].	34 normal university students Age 18–30	To classify students based on visual or non-visual style.	-The participants need to watch the animated learning content. -Take two main tasks involved, namely, (1) the learning task and (2) memory or information retrieval tasks.	-The alpha and gamma waves showed great agreement for the learning process to distinct the visual and non-visual learners based on power spectral density features.
Performance and learning level	Eroğlu et al. [113].	One dyslexic boy Age 14	To improve students' ability in reading and cognitive function.	-Using AutoTrainBrain apps by watching and listening to real-time multimedia for 10 minutes each week for nine weeks.	-The results showed improvement in cognitive function using brain training system based on three measurements, namely, (i) estimation of single-channel EEG, (ii) connectivity between two channel in spectral brain, and (iii) single channel in alpha waves.
Sleep	Komarov et al. [114].	18 normal university students (10 male and 8 female) Age 24.0±1.2	To measure sleep quality, stress, and self-assess fatigue.	-Do the daily report DSS during the academic year through smartphones.	-The outcome proved that regular fatigue levels are positively related to stress and sleepiness (during the day) as well as sleep quality.
Self-efficacy	Sun and Yeh [115].	80 normal university students (43 male and 37 female) Mean age 23.55.	To provide biofeedback when a student's attention is low.	-Participants need to read the content about anti-phishing. -When completed, need to answer the post-test learning self-efficacy scale and learning achievement test.	-The learner's attention can be depend on EEG biofeedback and the selection of the course topics.
Learning behavior	Nassar et al. [116].	39 normal university students (17 male and 22 female) Mean age 20.2.	To examine and measure the learning behavior based on predictive inference task using P300.	-Participants need to put the shield on position to catch the cannonball and then perform the same task without seeing the cannonball position.	-The results showed that the P300 signal was interpreted differently according to the statistical context in the learning processes to calibrate learning in complex environments.

TABLE 2. (Continued.) Potential articles sorted by learning influence factor.

Motivation and interest	Daly et al. [117].	23 normal university students (10 male and 13 female) Mean age 20.	To investigate motivation during solving mathematic problems.	-Participants need to notify the motivation level before and after test. -Participants answer mathematical problems.	-Mathematical mindset theory boosts motivation, and this transition is expressed in learners' mathematical brain activity problems.
Emotion	Solomon et al. [118].	31 normal children (14 boys and 17 girl) Age 5-7.	Emotional interference on attention.	-Children see faces (angry, happy, and neutral) to generate emotions for measuring the EEG.	-More attention intervention with angry faces showed greater negative affectivity with greater right anterior-temporal asymmetry from the children. -Less attention interference with neutral faces showed greater negative affectivity with greater left posterior asymmetry from the children.
Stress	Maddox et al. [119].	19 normal participants (6 medical students, 9 urology residents, and 4 attending urologists).	To measure stress and attention for surgeon/medical students.	Participants need to perform laparoscopy based on a simulation to measure stress and concentration during the surgery.	-Stress in participating urological practitioners was substantially lower than in laparoscopic suturing compared with residents and medical students in the peg transfer task. -In the expert group, concentration was much higher than in the less experienced group during the peg and suture tasks.
Learning Environment	Bevilacqua et al. [120]	12 normal senior high school students and teachers (5 male and 7 female).	To understand the relationship between brain-to-brain (teacher and students) and classroom learning.	-Classroom activities with two teaching styles, namely, (i) face-to-face and (ii) recorded session. -Students need to answer 20 questions after the recorded session.	-The finding demonstrated social factors, such as perceived proximity, in real-world community settings, brain-to-brain synchronization, and cognitive effects, such as students' academic performance, which can be expected.

Note: **BCI** – brain-computer interface; **EEG** – electroencephalogram; **ADHD** – attention deficit hyperactivity disorder; **LD** – learning disabilities; **(F- NF)** – frequency neurofeedback; **DSS** –daily sampling system; **MOOC** – massive open online course. \* Denote that this paper has contradicted results from neuromyth.

a successful way to improve cognition, social contact, behavior, and emotion learning. However, based on our review, only 22 studies focused on students with disabilities from children to university and college students. Some of the students with these constrictions might have difficulty in being a participant. Additionally, researchers need to get ethical approval from the Institutional Review Board and consent from the parents, doctor, or hospital asking them to participate in the experiment, which might have been a complicated process. Moreover, wearing the BCI tools might be uncomfortable for some students. However, if this type of student volunteers as a participant more in the future, all stakeholders will reap the benefits because they can receive the neurofeedback report of the student performance and the influencing factors, such as memory, concentration, relaxation, or emotion from the BCI [127]. This feedback system will allow them to understand the students better and suggest the best way for enhancing the learning or getting a suitable treatment. For neuroeducation research, this is the advantage to suggesting new policies to be implemented in the education system.

The cognitive process factor is the prevalent factor, particularly for attention, probably because of its importance in learning. It includes various cognitive processes, including filtering critical information, controlling mental energy while performing a task, and handling the mind to focus at a specific duration time. This influencing factor showed the largest number of publications for the disabled category and do not have a specific task to evaluate attention, and most of them used a game as the task [128]–[130]. This may be because games are more interactive, fun, and exciting, especially for children. Zhang [107] also discussed measuring student concentration using web-application based on English vocabulary. The students need to understand the words and then click the word if it belongs to the animal category; in the study, the author showed a significant improvement in the small number of participants only in China.

Meanwhile, confusion remains poorly considered as an influencing factor in learning. These factors are highly influential in the clinical and psychological fields. If people are confused for too long, it can lead to dementia [131]. Dementia is a progressive disorder caused by deteriorating brain function and a loss of regular cognitive capabilities. EEG technology was used to classify students' confusion using a supervised learning classification system in the e-learning environment [108]. The authors classified parts of the video in which students make great mental efforts. To boost learning performance, students and teachers can access these segments. It can help the teacher explain a matter in simple terms so the student can understand more.

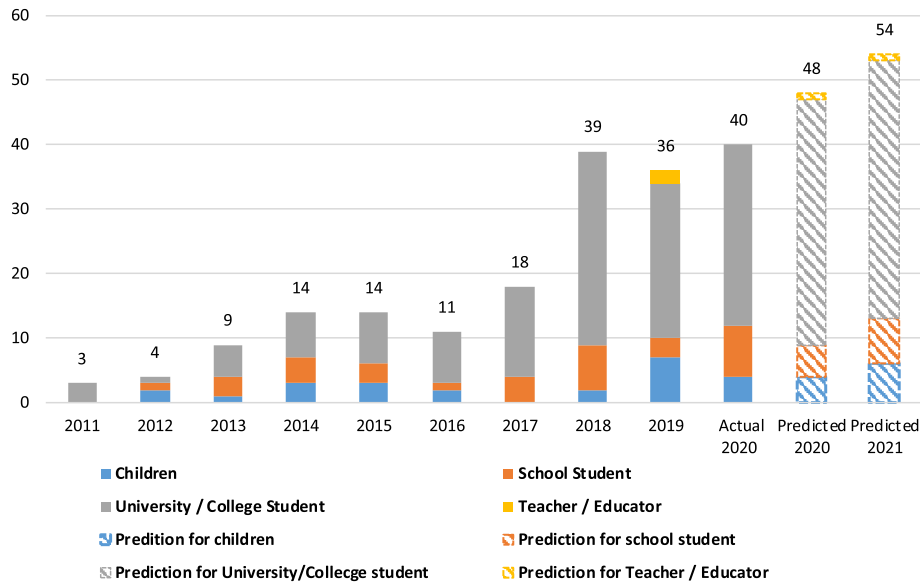
EEG responses were recorded to compare the memory and attention performance between children with learning disabilities and control children [109]. Children with learning disabilities reported lower delta response, which affected the deficit in information processing. This paradigm was suitable for studying the semantic contravention. Despite this, Hillard *et al.* [110] showed that the frontal theta and beta ratio

have a similar trend to measure focus of children with ADHD. This measurement can be achieved with smaller number of sessions. It can be beneficial to reduce tiredness, and the children do not have to attend the long session.

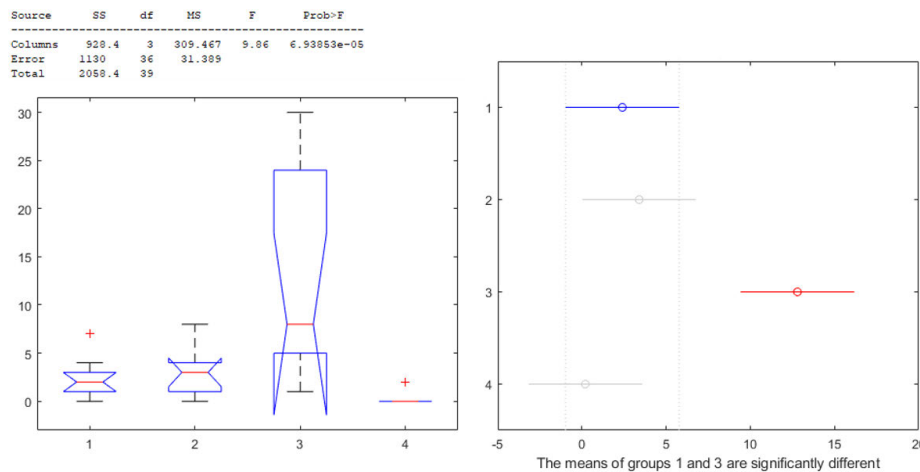
In contrast, only one testbed related to aerobic and treadmill exercise evaluated the brain function of students [132]. The results showed that moderate intensity could normalize the theta and beta ratio for children with ADHD compared with the condition while watching the video. The results from Vollebregt *et al.* [111] showed no significant improvement for the frequency of neurofeedback while watching the video, suggesting that any kind of exercise can strengthen concentration and memory and encourage students to become more diligent and remember what they learned in the classroom.

Dekker *et al.* [59] found that over 90% of teachers unfortunately believe in learning styles, and Dandy and Bendersky [133] showed that over 60% of teachers think that teaching to students' learning styles can help the students to learn in more efficient way. In addition, few researchers still believe also that learning style is one of the individual and behavioral factors in education. These researchers have used assessment method (Kolb's Learning Style Inventory (KLSI), [134]) for the measurement of learning style to understand the preferred way of learning [135]–[138]. Two publications about learning styles [112], [139] have been published in Journal of Engineering and Applied Sciences and Frontiers in Behavioral Neuroscience, respectively and can be found in SCImago (journal indexer). Both of these publications have claimed that learning styles can be measured from the brain activity using EEG measurement. For instance, Jawed *et al.* [112] have classified students based on visual or non-visual learning styles. The students watched the video and/or hear the audio during the testbed to recall the memory. Teaching and learning process require complex brain functions which cannot be oversimplified within three learning styles groups. Although people do have preferences for how they learn, or ways they like to learn the best, presenting information in several different ways for all students is an important educational practice for the brain. The brain requires the coordinated use of seeing, hearing, and doing in many learning situations (learning new language). Furthermore, students in learning process involve additional skills such as memory, emotion, motivation, thinking, and imagination [140].

Although the influencing factor should be covered for all the disabled groups, only two publications from this review studied the performance of children with dyslexic [113] and students with internet addiction for university or college students [141]. In addition to university students, people across different ages can also face problems with internet addiction because of the proliferation of the digital world, which is the main issue here. The obsession with the internet might have a negative effect on academic performance. This could be a growing problem as students need to use the internet for long stretches owing to of COVID-19 because most formal education has transferred to the e-learning or hybrid learning.



**FIGURE 4.** Publication trends for using cognitive and affective BCI in education to measure the influencing factors.



**FIGURE 5.** Publication class box plots using one-way analysis of variance (ANOVA) in the left and the results of Scheffé’s multi-comparison test in the right. The central mark in each class (four classes: papers relate to children, university/college students, school students, and teachers/educators) corresponds to its median, the edges of the boxes are the 25th and 75th percentiles, the whiskers extensions are the most extreme data points, and “+” markers correspond to the outliers.

We consider that this will be beneficial for neuroeducation to measure how the brain adapts the new learning as well as the emotion of students when they have limited access of seeing the teacher to discuss a study-related matter.

According to Komarov *et al.* [114], university students are systematically affected by stress and unusual sleep cycle while handling the assessment. This demonstrates that the significance of daily fatigue contributes to stress and anxiety. The sample result was only focused on normal subjects, which can be biased against the students who have disabilities. Furthermore, the method will take much time (throughout the whole semester) and record daily sessions.

Self-efficacy is another factor that can influence the learning process. As explained by Sun and Yeh [115], real-time EEG feedback for self-efficacy can be measured while monitoring the attention for learning. Despite this, in their study, the authors only provided the audio feedback, and the material was limited to one topic about anti-phishing. Notably, the learning behavior stated by Nassar *et al.* [116] justified that the students are flexible to adjust the learning based on the environmental statistics. However, the real-world environment varies enormously over a lifetime, and the cognitive capacity for learning process can be changed based on age. Additionally, there is increasing evidence that

neighborhood poverty plays an important role in cognitive function [142].

In the Affective factor, the BCI helps identify the student's motivation and interest based on the learning material, such as multimedia-based mobile learning and reading texts from Russian literature [143], [144]. This can help the teacher adjust the content based on the cognitive load and student interest. If the content is something the student likes, it will motivate them to learn more and focus. Additionally, Daly *et al.* [117] suggested that teachers present mathematical problems conceived as a mathematical mindset problem. A combination of behavioral and neurophysiological measurements showed students' motivation level in a mathematical mindset.

Additionally, the student often feels stress during exams [145], and reducing the stress can improve academic performance and exam results. With the BCI report's feedback, the education system can work together with therapists for student treatment. Maddox *et al.* [119] demonstrated the effects of stress measurement between expert and intermediate or novice surgeons. The surgeon with experience showed more concentration and less stress compared with the new surgeon, which was because of the expert's serving years of experience. The researchers only focused on medical students with laparoscopic techniques. Therefore, there is a significant correlation between emotion and concentration [146], and emotion can influence the learning process too. Solomon *et al.* [118] observed emotion in young children using EEG asymmetry to examine the changes in the emotions based on negative affectivity. The results showed gender differences between boys and girls and concluded that the boys have a larger degree of anterior asymmetry on the right, whereas females exhibit a greater degree of anterior asymmetry on the left.

Finally, the learning environment should be considered. Facilities, lighting, or ventilation can affect student performance. However, the learning environment does not necessarily have to be in the classroom. Any comfortable place is enough, and as long as knowledge transfer exists, it can be a part of education [147]. The BCI can help to evaluate the comfort situation for the transfer of knowledge and learning purposes. Bevilacqua *et al.* [120] reported the transfer of knowledge between teachers and students via inter-brain coherence to examine the classroom's social interaction using EEG in task-based biology lessons with different teaching styles (lectures and videos). The findings reported that the student with greater social closeness to the teacher produced higher brain-to-brain synchronization which means have a similarity between brain region during the social interaction. Teachers should understand the student engagement level to improve the method of teaching. The environment plays the huge role implications in the development of neural pathways in the brain that support learning. Ozernov-Palchik *et al.* [148] study shows the children from families of lower socioeconomic status (SES) tend to have poorer reading performance. Reading relies on the orchestration of

multiple neural systems integrated via specific white-matter pathways.

Most neuroscience and neuropsychology studies have been trying to understand the brain mechanisms for some specific cognitive n affective daily life tasks such as calculation, reading, talking, and problem solving [149], [150]. Example, reading comprehension is a complex task that depends on multiple cognitive and linguistic processes. In adults with dyslexia, individual variation in reading comprehension can be largely explained by combined variance in three component abilities: decoding accuracy, fluency, and language comprehension [151]. While Beach *et al.* [152] purposed to assess the (dis)similarity of brain response patterns elicited by two distinct activities using neural decoding for brain mechanisms. These studies indirectly improve the education outcomes because they give a clear vision to understand and solve students' cognitive and affective difficulties like students have a problem paying attention or concentration, having a sleep problem, or feeling stress.

Neurofeedback-based BCI applications directly impact education and learning outcomes such as for ADHD, autism, or dyslexia. In addition, these include the treatment of ADHD, autism, or any students with disabilities with positive behavior supports (for example, family involvement, school-based solution-focused, behavioral group interventions) as well as intervention strategies (for example, organizational and social skills training ) and other interventions (for example, academic accommodation facilities and self-management) [153].

Other BCI applications such as controlling wheelchairs or browsing the internet can remove the barrier of handicapped people to continue learning. The BCI advanced technologies benefit their well-being by minimizing their reliance. For example, internet and web browsers have drastically impacted people's daily communication and one of the sources of information. As a result, it becomes reasonable to make the Internet accessible to individuals with limited communication abilities to enhance their autonomy and learning process, consequently, their quality of life. [154].

In addition, during the COVID-19 pandemic, the widespread use of online and e-learning systems has become a significant challenge for the education system. The face-to-face method shifted to distance learning to halt the virus's spread and suspended school and university attendance. These decisions have had a significant impact in the areas of education, interpersonal interactions, and student wellbeing, and mental health [155]. Consequently, the BCI system can be utilized to enhance the distance learning performance [156] and examine the students' performance and mental health when the learning process transitions from face-to-face to online learning [157]. With the changing of technology to online learning, different skills are needed, especially for teachers and educators. Micro-credentials give teachers the chance to do rigorous and self-reliant tasks linked to the conversational skills teaching requires in the classrooms. This new wave of professional learning offers teachers a method



TABLE 3. References sorted by participants in Normal and Disabled category.

Participant	References	Total	
Normal	Children School	[123]; [109]; [118]; [124]; [160]; [125]; [161]; [162]; [163]; [164]. [165]; [166]; [167]; [168]; [169]; [170]; [171]; [172]; [173]; [174]; [175]; [176]; [177]; [178]; [179]; [180]; [181]; [182]; [183]; [184]; [185]; [186]; [187]; [120]; [35]; [188]; [189]; [190]; [191]; [192]	10 30
	University / College Student	[193]; [194]; [195]; [196]; [197]; [198]; [199]; [200]; [201]; [202]; [203]; [204]; [205]; [206]; [207]; [48]; [208]; [209]; [115]; [210]; [211]; [212]; [213]; [214]; [215]; [167]; [216]; [217]; [218]; [219]; [220]; [119]; [221]; [222]; [108]; [223]; [224]; [225]; [226]; [227]; [228]; [176]; [229]; [230]; [231]; [232]; [233]; [234]; [235]; [236]; [237]; [238]; [239]; [240]; [241]; [242]; [243]; [244]; [245]; [246]; [247]; [248]; [249]; [250]; [251]; [139]; [135]; [112]; [138]; [252]; [253]; [254]; [255]; [256]; [257]; [258]; [259]; [136]; [260]; [137]; [261]; [262]; [263]; [264]; [265]; [266]; [267]; [268]; [114]; [269]; [270]; [117]; [271]; [116]; [272]; [273]; [141]; [274]; [143]; [275]; [276]; [144]; [277]; [278]; [279]; [280]; [281]; [282]; [283]; [284]; [285]; [145]; [286]; [287]; [288]; [289]; [290]; [291]; [292]; [293]; [294]; [295]; [296]; [297]; [298]; [299]; [300]; [301]; [302]; [192]; [303]; [304].	132
Disabled	Teacher / Educator	[281]; [120].	2
	Children	[109]; [305]; [105]; [128]; [129]; [130]; [306]; [307]; [110]; [132]; [308]; [113]; [162]; [111]; [309]; [163]; [164].	17
	School Student	[310]; [311]; [190].	3
	University / College Student	[107]; [141].	2

TABLE 4. References sorted by four main influence factors for this review.

Influencing factor	References	Total	
Cognitive Process	[123]; [109]; [118]; [124]; [165]; [166]; [167]; [168]; [169]; [170]; [171]; [193]; [194]; [195]; [196]; [197]; [198]; [199]; [200]; [201]; [202]; [203]; [204]; [205]; [206]; [207]; [48]; [208]; [209]; [115]; [210]; [211]; [212]; [213]; [214]; [215]; [305]; [105]; [128]; [129]; [130]; [306]; [307]; [242]; [216]; [217]; [218]; [219]; [220]; [119]; [221]; [222]; [172]; [173]; [174]; [160]; [108]; [223]; [175]; [224]; [225]; [226]; [227]; [228]; [176]; [110]; [229]; [230]; [231]; [232]; [177]; [125]; [233]; [234]; [235]; [236]; [237]; [238]; [239]; [240]; [241]; [107]; [243]; [244]; [245]; [246]; [247]; [248]; [249]; [250]; [178]; [179]; [180]; [161]; [162]; [132]; [308]; [113]; [111]; [310]; [311]; [309]; [290]; [292]; [294]; [295]; [296]; [297]; [298]; [188]; [299]; [163]; [300]; [301]; [302]; [190]; [192]; [303]; [164].	119	
	Individual and Behavioral	[251]; [139]; [135]; [112]; [138]; [252]; [253]; [254]; [255]; [257]; [256]; [258]; [259]; [136]; [260]; [137]; [261]; [243]; [262]; [263]; [264]; [265]; [266]; [267]; [268]; [181]; [182]; [183]; [113]; [114]; [269]; [270]; [184]; [117]; [115]; [271]; [116]; [272]; [273]; [141]; [35]; [189]; [191].	43
	Affective	[274]; [244]; [117]; [143]; [275]; [276]; [144]; [277]; [204]; [278]; [279]; [280]; [185]; [186]; [187]; [304]; [118]; [281]; [119]; [224]; [282]; [283]; [284]; [114]; [285]; [145]; [270]; [286]; [287].	29
	Environment	[120]; [288]; [289]; [291]; [293]; [163].	6

of gaining acknowledgment for their abilities through formal and informal learning possibilities, personalizing and applying their professional training during the teaching-learning process with the students [158].

The neuroscientists and neuroeducation researchers have to solve many open questions and assess the effectiveness of BCI applications in improving learning strategies and enhancing cognitive capabilities. For instance, the potential of BCI technology for education remains unclear and more neuroscientific experiments must be done before suggest the new policies and to overcome the myths issues in education. For instance, it is not yet proved whether BCI technology is needed in the classroom for teachers to monitor student attention or do teachers already know which students are paying attention. In addition, until today there is no evidence that such technology is beneficial for student outcomes. Further studies should investigate in the correlation between student outcomes and the use of BCI. The ethical issue of using such a technology with children remains debatable.

#### A. REVIEW LIMITATION

This SLR might have several limitations that need to be acknowledged. First, there was heterogeneity in measurement for influencing factors, purpose, and tasks. This review comprises mainly participants from university and college environments, and the results from children are limited because the search string did not include the word “children.” Additional limitations include the scope for this review that focuses on formal education. Second, this review does not examine neuroethics in education to monitor the student’s brain. Personal details concerning the student may be needed to ensure the participants’ protection or to comply with any specified requirement for using neuroimaging in neuroeducation research. Consequently, the confidentiality of participants was not covered in this review. Third, the articles included in this review focused on the task, regardless of the type of BCI application, tools, or EEG equipment. Future studies are recommended to include different BCI equipments to analyze the differences in impact of influencing factors. Additionally, refinement to explore security and privacy issues provided by different companies to protect users’ private information is required. Recently, several brain measurements’ companies, such as BitBrain Technologies, Interactive Brainwave Visual Analyser, g.tec medical engineering GmbH, and Emotiv, have been working on BCI and education ([http://bnci-horizon-2020.eu/images/bncih2020/FBNCI\\_Roadmap.pdf](http://bnci-horizon-2020.eu/images/bncih2020/FBNCI_Roadmap.pdf), [http://bnci-horizon-2020.eu/images/bncih2020/Roadmap\\_BNCI\\_Horizon\\_2020.pdf](http://bnci-horizon-2020.eu/images/bncih2020/Roadmap_BNCI_Horizon_2020.pdf), [159]). These companies have been focusing on some neuro-education topics and developing some user-friendly, wearable, portable, and wireless brain equipment in the market, such as Unicorn Education Kit (g.tec medical engineering, Graz, Austria).

#### V. CONCLUSION

This SLR examined various studies concerning the influencing factors in learning processes using EEG and

participant groups. We classified influencing factors into four categories—(i) cognitive process factor, (ii) individual and behavioral factor, (iii) Affective factor, and (iv) environment factor—with two groups of participants, namely, (i) normal and (ii) disabled. There is a positive outcome of developing more BCI applications for education and learning to measure students’ cognitive abilities. The results showed that the interest in using BCI for educational purposes is promising, indicated by various measurements of influencing factors to enhance academic performance. Although the BCI can significantly impact the education field, its implementation should be driven by following policies for effective education and healthy pedagogy.

With the current situation of the COVID-19 pandemic, education systems are being disrupted, and schools and institutions’ closures have impacted the student population worldwide. This crisis has challenged school systems, and students have had to tap into their own resilience and resources to continue learning. Teachers also had to adjust to new pedagogical principles and a flexible style of delivery. Under these circumstances, students can face a negative impact on wellbeing and emotions. Neuroeducation could be used as a backbone, especially for teachers, for understanding the student brain to support future academic success in any circumstance.

This review identifies the influencing factors that serve to enhance the learning process using BCI. Our future work will continue to examine the learning environment, especially online learning, which can impact the learning process and students’ enthusiasm for the new adapted norm. We aim to continue promoting the use of BCIs in the field of education.

#### APPENDIX

See table 3 and 4.

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**NURAINI JAMIL** received the B.Sc. degree from the University Technology of Malaysia and the M.E. degree in information engineering from Inha University, South Korea. She is currently pursuing the Ph.D. degree with United Arab Emirates University, working under the supervision of Dr. Belkacem. Her research was related with image processing for natural scene. Her current research interest includes brain–computer interface. She is particularly interested in the brain–computer interface for education and mental health of student.



### ABDELKADER NASREDDINE BELKACEM

(Senior Member, IEEE) received the Ph.D. degree in information processing from Tokyo Institute of Technology, Japan, in 2015. He is currently an Assistant Professor with United Arab Emirates University (UAEU). Prior to joining the UAEU, he was a Specially Appointed Researcher with the Department of Neurosurgery, Osaka University Medical School, and an Assistant Professor with the Endowed Research Department of Clinical Neuroengineering, Global Center for Medical Engineering and Informatics, Osaka University, Japan, from 2015 to 2019. His research interests include brain–computer/machine interface using human magneto- and electroencephalography (MEG/EEG), human–machine interaction, artificial intelligence, robotics, and neuroscience. He was one of the recipients of the prestigious international award "MIT Technology Review Innovators Under 35 MENA" and brings over ten years of experience in brain–machine interface (BMI). One of his work was adopted on a cover page of IEEE TRANSACTIONS ON NEURAL SYSTEMS AND REHABILITATION ENGINEERING, Volume 26-6, 2018. He has been a Vice Chair of the IEEE P2725.1 Working Group, since 2021. He has contributed in many international technical program committees, such as IEEE International Conference on Systems, Man, and Cybernetics (SMC2018/20/21) as the Co-Chair of BMI workshops. He is a Guest Associate Editor of BMI on journal of *Frontiers in Human Neuroscience*.



### SOFIA OUHBI

received the Ph.D. degree in software engineering from ENSIAS, Morocco, in 2015, and the Ph.D. degree in software engineering from the University of Murcia, Spain, in 2017. She is currently an Assistant Professor with UAEU. Prior to joining UAEU, she was an Assistant Professor with the International University of Rabat and was a Visiting Researcher with the IT University of Copenhagen, Denmark. She has an active participation in organizing and chairing conferences and she has experience as a Peer Reviewer for journals indexed in Scopus and Web of Science. She has coauthored more than 40 publications in peer-reviewed conferences and JCR journals. She has intersectoral skills through work experience both in academia and industry (in Hewlett-Packard 2009–2011). She has contributed to many national and international research projects and technology transfer contracts whose topics were related to software engineering and health informatics.



### CHRISTOPH GUGER

(Member, IEEE) received the Ph.D. degree from the Department of Medical Informatics (Prof. Pfurtscheller), University of Technology Graz, in 1999. He studied biomedical engineering at the University of Technology Graz and Johns Hopkins University, Baltimore, MD, USA. He then carried out research work at the Department of Medical Informatics (Prof. Pfurtscheller), University of Technology Graz. The topic of his Ph.D. work was the design of an EEG-based brain–computer interface. This was the first real-time BCI system with continuous feedback. He also developed the real-time analysis with common spatial patterns, which is still the fastest and most accurate approach for oscillatory BCIs, and also developed a P300 BCI with very high accuracy and speed. In recent years, he also worked with ALS and tetraplegic patients in different countries. He co-founded g.tec, in 1999, and has been working there ever since. He has dozens of peer-reviewed publications, including three open access publications in *Frontiers in Neuroscience* that he led (and coauthored with Dr. Edlinger). He was awarded the internationally recognized EY Entrepreneur Award.