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Neurotechnologies in educational Contexts: A Systematic Literature Review

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ABSTRACT: *In recent years, the use of neurotechnologies in education has gained prominence as a promising approach to enhancing peda-gogical practices, particularly in areas related to Science, Tech-nology, Engineering, and Mathematics (STEM). This systematic literature review (SLR) covers the period from 2019 to 2024 and was conducted using the Web of Science, IEEE, and Scopus databases. The aim was to identify the main justifications for incorporating these technologies into pedagogical practice, the types of tools employed, and the benefits reported in recent research. The review followed the PRISMA methodology, focus-ing on both technical and educational aspects. Seven studies were included, highlighting the application of technologies such as EEG (electroencephalogram), fNIRS (Functional Near-Infrared Spectroscopy), and eye tracking. The results show that these tools allow for the monitoring of cognitive and emotional processes, enabling personalized adjustments to materials and pedagogical strategies. Moreover, brain-computer interfaces (BCIs) have been employed to enhance learning and support students with specific needs through the use of machine learning algorithms to analyze neural data, enabling the creation of adaptive systems that adjust content and teaching pace in real time. Such approaches make education more effective, inclusive, and tailored to students' individual needs. We conclude that neurotechnologies have great potential to transform education by providing relevant data on learners' neural and emotional activity, promoting more engaging and efficient learning.*

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I. Introduction

In recent years, neurotechnologies have received growing attention [1], [2], [3], [4], [5], [6]. In the educa-tional context, investigating brain activity during learning tasks has significantly contributed to the improvement of teaching and learning processes [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], data analysis [14], [16], [18], [19], and the development of intelligent educational systems [12], [13], [20], [21], [22], [23], [24], [25], [26], [27], [28]. These technologies have proven particularly promising in STEM (Science, Technology, Engineering, and Mathematics) learning environments [29], [30], providing an integrative approach to evaluating students' interactions with various educational resources and meth-ods.

This approach offers educators valuable pathways for recognizing physiological signals [31], [32], which can positively impact the promotion of more effective learning. This is especially relevant in educational settings, where recognizing students' brain activity responses can enhance the learning experience [7], [8], [33], [34], [35], [36], [37], [38], [39].

The use of portable devices, which combine non-invasive approaches with lower operational complexity, has facilitated research in real educational contexts [40]. Devices such as wearables equipped with electroenceph-alography (EEG) and functional near-infrared spectrosco-py (fNIRS) technology allow spontaneous recording of brain activity during learning sessions [41], [42], [43], [44], using sensors positioned on the scalp [45]. This tech-nology provides educators with tools to recognize physio-logical signals that can promote more effective and per-sonalized learning, enhancing students' experiences [40], [43], [46], [47], [48], [49], [50], [51], [52], [53].

The growth of the neurotechnology market, projected to exceed 21 billion dollars by 2026, underscores its potential impact beyond healthcare, spanning from neurological treatments to innovative educational applications [5]. Its widespread adoption could have substantial and immediate impacts, particularly in brain research, where data collec-tion was traditionally controlled and restricted to laborato-ry settings [40].

Although considerable advances have been made, gaps still exist regarding the justifications, tools, and benefits of using neurotechnologies in the educational process. For this reason, a systematic literature review is essential to explore the state of research over the past five years on the use of neurotechnologies to acquire brain activity data in learning contexts. Specifically, we are interested in studies focusing on STEM education. Examining STEM education is relevant because it provides an interdisciplinary ap-proach to analyzing how students interact with various educational resources and methods, fostering advance-ments in teaching practices and understanding learning processes in these fields.

The review covers the period from 2019 to 2024, chosen due to the rapid evolution of neurotechnologies and their application in educational contexts. Limiting the analysis to the past five years captures the most recent and relevant advancements, considering that technology develops rap-idly, making older data potentially obsolete. This timeframe reflects current technical and pedagogical pro-gress, allowing the identification of emerging trends and research gaps. Searches conducted on IEEE, ScienceDirect, and Web of Science platforms revealed no prior systematic reviews specifically addressing the use of neurotechnolo-gies in STEM educational contexts. However, related re-views on neuroscience in education, a parallel theme, were identified, reinforcing the relevance and originality of this investigation by exploring a specific and underexplored focus.

The main findings and contributions of this work can be summarized in three key aspects. First, the role of monitor-ing cognitive processes in STEM education stands out, enabling personalized adjustments to materials and teach-ing strategies. Second, the use of brain-computer interfaces (BCI) as an educational tool demonstrates potential for enhancing learning and supporting students with specific needs in these contexts. Finally, the application of machine learning algorithms in analyzing brain data in STEM pre-sents a promising approach, enabling the development of adaptive systems that adjust content and teaching pace in real time.

The remainder of this paper is structured as follows. Sec-tion II outlines the methodological process adopted for conducting this SLR. Section III presents an analysis of the data obtained from the conducted research, providing an overview of the collected records. In Section IV, we provide a qualitative analysis of the SLR findings, address-ing the proposed research questions, discussing key find-ings and their implications in the educational field, high-lighting the most relevant results, and their potential reper-cussions based on other studies in different areas. Finally, Section V concludes the paper by synthesizing final re-marks and projecting future work using the collected in-formation.

Thus, this work aims to expand the understanding of the role of neurotechnologies in monitoring educational activi-ties, especially in STEM education, and how they can be used to improve the learning experience in a transdiscipli-nary manner.

II. Research Methodology

In the field of educational technology, conducting an SLR plays a crucial role in systematically identifying and synthesizing references from previous studies to answer specific questions and apply the obtained knowledge to new contexts. For this purpose, we adopted the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology[54], using a structured approach comprising different stages: searching scientific databases, importing studies, study selection, quality evaluation, data extraction, and data analysis, as shown in Fig. 1.

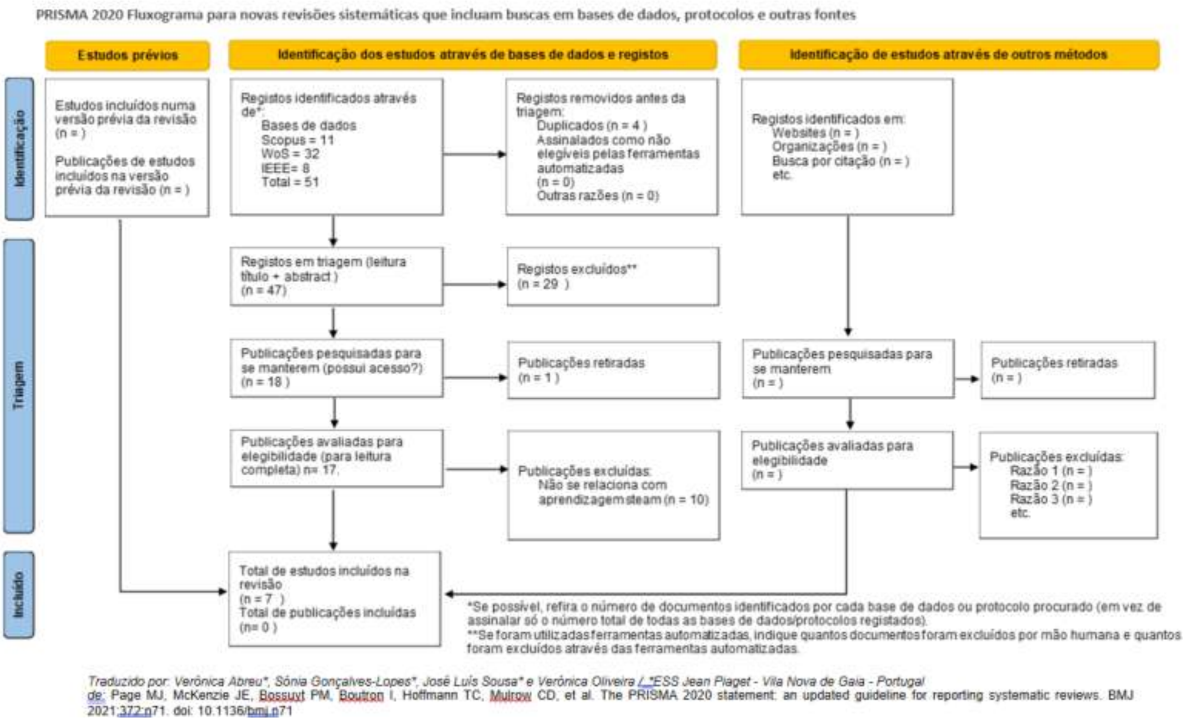

FIG. 1. PRISMA 2020 FLOW DIAGRAM.

The Parsif.al platform was used to plan, organize, and manage the stages of this work, ensuring efficient structuring. The details of the process can be accessed at https://ufrgscpd-my.sharepoint.com/:f:/g/personal/00330497_ufrgs_br/Era0t1pk3CBMlpcMH-F9ugcBgHh1mo7rrP1ZXy_z6WUhsQ?e=o4JlMc.

The first step involved formulating a central research objective, which aimed to understand how the use of EEG-based neurotechnologies impacts the educational process in STEM contexts. From this objective, research questions were developed to guide the search and analysis of scientific articles.

The search strategy employed in this research consisted of using a query string to conduct automated searches in databases containing technical and academic literature. This string was formulated considering the main terms related to the research objectives. The review protocol development highlighted terms associatedto the population, intervention, comparison criteria, outcomes, and context, known as PICOC, focusing on identifying primary studies.

Research Questions

To deepen the analysis and ensure a comprehensive perspective, a two-pronged approach was adopted: exploring technical aspects to identify and map the types of technologies used in the educational field, including the specifics of devices and methods employed; and examining application contexts to explore the educational settings where these technologies were implemented, analyzing the reasons for their adoption, reported benefits, and correlating these findings with studies achieving similar results in other education-related areas. This analytical frameworkwas guided by three main questions, detailed in Table 1, which served as a reference toidentify patterns, gaps, and future research opportunities.

Research Questions		
RQ1	What are the main tools used?	Technical aspects
RQ2	What are the main justifications for using neurotechnologies in the STEM teaching and learning process?	Pedagogical aspects
RQ3	What benefits of using neurotechnologies in the STEM context have been reported?	

TABLE 1. RESEARCH QUESTIONS

Search Platforms

Sources considered included platforms such as IEEE Digital Library, Science@Direct, and Web of Science. The search strategy was guided by the string "STEM" OR "STEAM" AND "education" AND "neurotechnology." The inclusion of the term STEAM aimed to explore the integration of Arts (A) into the fields of Science, Technology, Engineering, and Mathematics (STEM), a movement that seeks to broaden the educational focus by incorporating creative skills and artistic practices. Although no studies using the term STEAM were identified in the searches, its inclusion was important to ensure that potential contributions involving broader and interdisciplinary approaches were considered. Figure 2 presents the distribution of retrievedstudies by database.

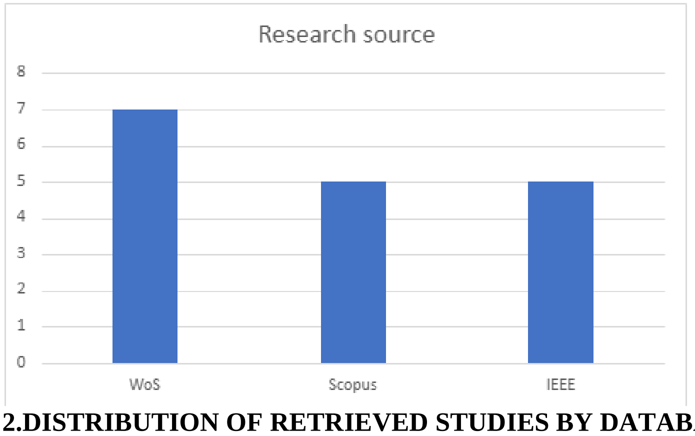

FIG. 2.DISTRIBUTION OF RETRIEVED STUDIES BY DATABASE

Inclusion and Exclusion Criteria

In terms of inclusion criteria, only articles published in Portuguese, English, and Spanish were accepted. The study prioritized primary works, peer-reviewed journals, published between 2019 and 2024. To ensure relevance, duplicate articles, studies unrelated to neurotechnologies in education, works that did not address neurotechnologies, publications without open access, and materials misclassified as articles were excluded, as shown in Table 2.

Inclusion criteria	**Exclusion criteria**
English, Spanish or Portuguese	Duplicates
Published between the years of 2019 and 2024	Not a primary article
Only in peer-reviewed journals	Not related to the educational process
	No direct access

TABLE 1. INCLUSION AND EXCLUSION CRITERIA

Study Selection Procedure

The structured method for study selection involved automated title searches in research databases, importing them into the Parsif.al application, totaling 51 titles. The built-in tool of the Parsif.al system was used to identify and exclude duplicate works from different search sources.

The next phase involved selecting works based on the inclusion and exclusion criteria, followed by reading titles and abstracts to identify patterns indicating alignment with the research objectives, classifying them as "accepted" or "rejected." In this stage, 17 articles were accepted for quality evaluation.

The 17 selected studies were conducted by 68 authors and co-authors from 47 institutions across 13 countries. Most authors (89.24%) participated in only one study, while 8 authors (11.76%) were involved in two studies. Figure 3 presents the geographic distribution of the research among the countries.

FIG. 3. GEOGRAPHIC DISTRIBUTION OF THE RESEARCH

Similarly, most institutions (39 institutions - 83.98%) were also involved in only one study, while 8 institutions (17.02%) participated in two studies. Additionally, research in this field was spread across 13 countries, with the USA (17 institutions), China (9 institutions), Japan (5 institutions), Ireland (3 institutions), and Australia, Malaysia (3 institutions each) being the most prominent, followed by Germany, Bulgaria, Canada, South Korea, Slovenia, the Netherlands, and the United Kingdom (1 institution each). Table 3 presents the distribution of studies by institution. The sum may naturally differ from the total number of studies due to multiple relationships among authors, institutions, and studies. This distribution highlights the roles of countries such as the United States and China in technological and educational innovation, with growing investments in research, and demonstrates the pursuit of relevance by Asian countries in this field. Although the participation of European institutions is more limited in this survey, it points to opportunities to strengthen international collaboration and promote a more diversified knowledge exchange.

Country	Institution(n)	Research(n)	Institutions
USA	17	10	Kennesaw State University, Stanford University School of Medicine; University of Nebraska-Lincoln; University of California; Illinois Mathematics and Science Academy;Northern Illinois University; Max Planck-NYU Center for Language; New York University; Columbia University and the Research Foundation for Mental Hygiene; New York State Psychiatric Institute; University of Florida;Trever Day School; Grace Church School; Kennesaw State University;University of Minnesota Rochester; California State University of Fullerton; John's University
China	09	02	University of Electronic Science and Technology of China;Chengdu University of Information Technology;Chongqing University of Posts and Telecommunications;Chengdu University of Information Technology;First Affiliated Hospital to Army Medical University;Chinese Academy of Medical Sciences; Qilu Hospital of Shandong Universit;Oncology Key Laboratory of Sichuan Province; Xinxiang Medical University;
Japan	05	01	Shonan Institute of Technology;Junior College of Aizu; Waseda University; Chiba University;Waseda University
Ireland	03	01	University College Cork; Athlone Institute of Technology; University of Limerick
Malaysia	03	02	Sunway University; Universiti Tun Hussein Onn Malaysia; Monash University Malaysia;
Australia	02	02	University of South Australia; Institute of Artificial Intelligence and Robotic
Slovenia	02	01	Primary School Muta ; University of Maribor
Germany	01	01	Max Planck Institute for Empirical Aesthetics
Bulgaria	01	01	EcologyKM Ltd;
Canada	01	01	University of Ottawa
South Korea	01	01	Univ. of Michigan; Hanyang Univ., Seoul
Netherlands	01	01	University Nijmegen
United Kingdom	01	01	School of Computer Science

TABLE 2. DISTRIBUTION BY INSTITUTION

With this approach, we aimed to create a solid framework to understand how neurotechnologies are being applied in monitoring and enhancing educational processes, providing valuable insights for future research.

The articles with the potential to answer the research questions were identified by applying a questionnaire for quality assessment of the remaining works. A set of five quality questions, with a scoring criterion, was adopted, encompassing three possible classifications: (1) Criterion: "Yes" / Score = 1; (2) Criterion: "Partially" / Score = 0.5; (3) Criterion: "No" / Score = 0.

The quality assessment questions include verification of whether the study describes tools or types of EEG devices, justifies the use of neurotechnologies in the teaching and learning process in STEAM or STEM contexts, reports specific benefits for the STEM or STEAM educational domain, is directly related to the educational field in these areas, and cites the context in which neurotechnologies are being used. The final score is calculated by summing the scores of the responses to the related questions. Articles selected for the data extraction phase met the minimum threshold, demonstrating adherence to the research scope, with a minimum score of five points. At this stage, 7 articles were selected and are summarized in Table 4, showing the publication years. Unique IDs were assigned to the selected articles according to their order of appearance in the text.

Paper title	Year
Investigating brain activity patterns during learning tasks through EEG and machine learning analysis [55]	2024
Utilization of EEG and fNIRS To Determine Neural Alignment in Educational Applications [56]	2023
Introducing neuroscience to high school students through low-cost brain computer interface technologies[57]	2020
Your Brain on STEM Video Lessons: Exploring Neurophysiological Patterns and Educational Engagement to Video Content[58]	2024
Stem education in eco-farming supported by ict and mobile applications[59]	2021
Exploring problem conceptualization and performance in STEM problemsolving contexts[60]	2020
Application of NeuroIS Tools to Understand Cognitive Behaviors ofStudent Learners in Biochemistry[61]	2020

TABLE 4. SELECTED PUBLICATIONS SOURCE

III. Analysis

In this section, data extracted from the articles that met the research question criteria are presented, with a quantitative analysis of the tools utilized, the types of devices used, and the reported benefits.
The first research question aimed to identify which tools were applied in the various studies. The most frequently occurring combinations were organized into three main groups, as illustrated in Figure 4.

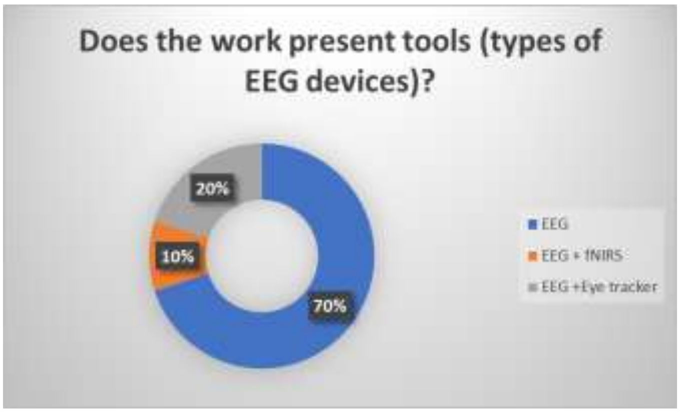

FIG. 4. TYPES OF NEUROTECHNOLOGY DEVICES

The most widely used method was EEG, present in four studies [55], [57], [59], [60]. The combination of EEG + eye tracker formed the second most relevant group, enabling detailed analyses of visual and cognitive interactions, which are particularly useful for investigating problem-solving and decision-making processes [58], [61]. The third group consisted of the combination of EEG + fNIRS, which integrated brain and hemodynamic data, allowing for more in-depth analyses [56].

Additionally, it was possible to identify several tools, including the Muse 2 EEG device (https://choosemuse.com) [55] , the EEG and fNIRS measurement systems Nautilus by g.tec (https://www.gtec.at) [56], [58], the OpenBCI EEG BCI (Brain Computer Interface) system (https://openbci.com) [57], the NeuroSkyMindwave EEG sensor (https://neurosky.com) [59], the Emotiv EPOC EEG sensor (https://www.emotiv.com) [60] and the use of a BiosemiActiveTwo EEG device (https://www.biosemi.com)paired with Tobii eye-tracking glasses (www.tobii.com) [61], as shown inFigure 5.

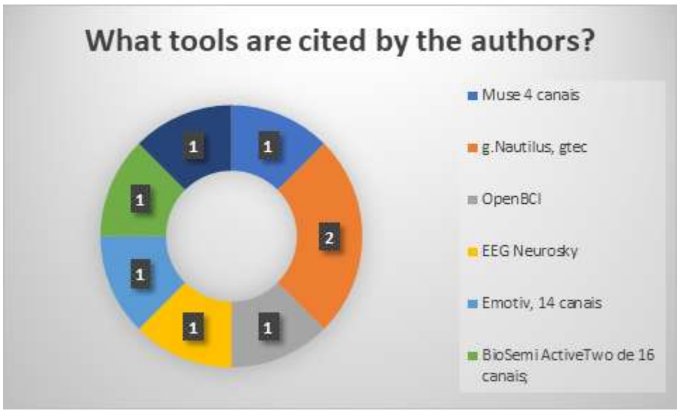

FIG. 5. DEVICES USED

The second research question aimed to understand the main justifications for using neurotechnologies in STEM contexts. For this purpose, we first sought to examine the population studied in each case and the intended outcomes. Regarding the educational levels where the research took place, the studies primarily focused on higher education [55], [56], [58], [60], [61], followed by high school [57] and professional education [59], as shown in Figure 6.

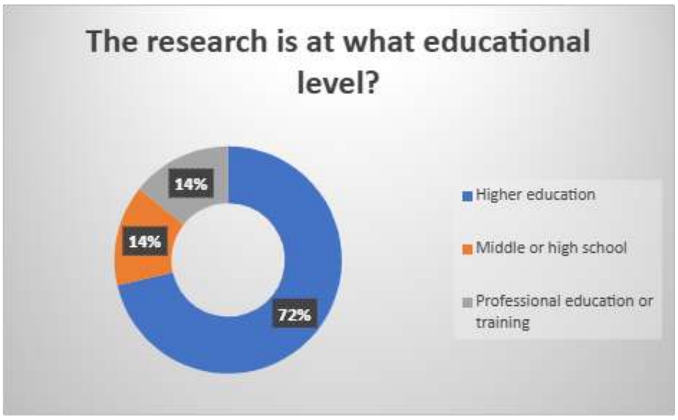

FIG. 6. EDUCATIONAL LEVEL

In higher education, notable applications included analyzing connections (or activations) between different brain lobes or monitoring activity during problem-solving tasks [55], [60]; monitoring neural alignment, attention, and engagement while individuals watched video media on various STEM topics [56], [58]; and monitoring and evaluating students' cognitive load as they engaged in classroom learning activities and manipulated biochemical models [61].

In high school, technologies were applied to promote interest in and literacy regarding in STEM fields among students during summer programs and to analyze real-time cognitive responses [57]. In professional education, the emphasis was on applied practices and developing skills related to environmental sustainability using mobile devices [59].

In STEM contexts, the use of neurotechnologies such as EEG, fNIRS, and eye trackers is widely justified by their ability to provide detailed data on students' cognitive and behavioral processes, enabling significant advances in teaching and learning in interdisciplinary areas. Across these studies, EEG was used to monitor brain activity during complex tasks, such as problem-solving and scientific concept manipulation, allowing the identification of connectivity patterns between brain regions, which are crucial for logical reasoning and working memory. According to the authors, these analyses help refine pedagogical strategies and develop teaching materials that promote higher engagement and enhanced student performance.

fNIRS, in turn, complements EEG by measuring hemodynamic changes associated with brain activity, providing an integrated view of neural responses to educational stimuli. This technology proved particularly useful for evaluating the effectiveness of pedagogical methods in STEM, contributing to a better understanding of how interdisciplinary learning affects students' neural processing and cognitive alignment. Eye tracking was employed to investigating students' visual interaction with educational materials, identifying elements that most captured attention and facilitated comprehension, thus enabling the development of more effective and personalized teaching resources.

Thus, different stimuli evoke distinct neural responses, generating patterns of brain activity characteristic of each individual. The analysis of these patterns, conducted using neurotechnologies, allows for the identification of similarities in how subjects process and respond to various types of information, revealing the neurophysiological foundations of perception and cognition [56]. By integrating this data into pedagogical practice, it is possible to develop more effective interventions, thereby optimizing teaching and learning processes in STEM. Furthermore, these tools promote the development of evidence-based pedagogical interventions that meet students' specific cognitive needs, maximizing their potential in different areas of knowledge.

Lastly, the third research question aimed to enumerate the benefits reported in each study. These findings reinforce the potential of neurotechnologies in monitoring and personalizing learning [55], [56], [58], [59], [60], [61], as well as providing alternatives for developing STEM topics through brain-computer interfaces [57], as shown in figure 7.

In [55], analyzing brain activity during different STEM activities allowed for a better understanding of the cognitive processes involved, highlighting significant connections between the frontal and temporoparietal lobes during these activities. According to the authors, this monitoring enables the restructuring of classes and materials to make them more engaging and adapted to specific thinking processes, considering aspects such as focus and students' zone of proximal development.

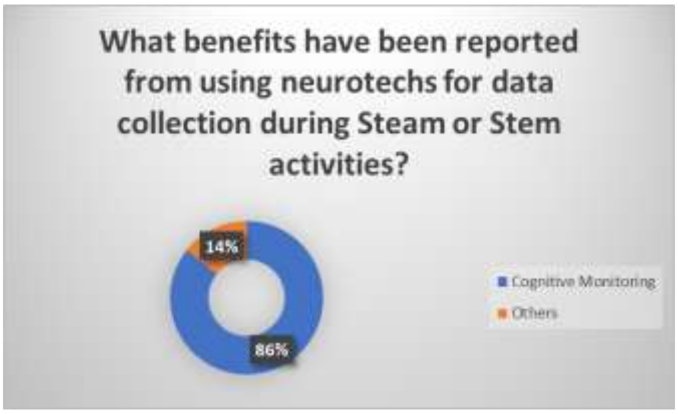

FIG. 7. BENEFITS REPORTED FROM USING NEUROTECHS

In [56], studies on neural alignment indicate that patterns in brain activity can be correlated with learning, identifying differences between subjects with and without prior knowledge of the content. This information helps researchers understand how different educational approaches impact neural processing and can be used to improve pedagogical practices. Furthermore, in[57] applying devices such as BCI systems proved an effective tool for increasing engagement and interest in careers related to neurotechnology and bioengineering. This is due to their ability to provide practical and interactive experiences that connect theoretical concepts of neuroscience and bioengineering to real-world applications. For instance, in the "BioEngineering Your Brain: Controlling the World with Your Brainwaves" program, students learned to use EEG devices to control computational interfaces, such as moving a character in a virtual maze using visually evoked potentials. This type of immersive approach not only sparked curiosity but also demonstrated how principles of biology, mathematics, and programming can be applied to solve real-world problems. Results from programs like this indicated a significant increase in participants' interest in studying biomedical engineering, neuroscience, and pursuing scientific research careers, in addition to offering students opportunities to develop technical, analytical, and creative skills, promoting not only learning but also a sense of achievement and belonging in science and engineering fields.

The use of EEG-based metrics and eye tracking[58] also showed promise in evaluating engagement and attention during exposure to educational videos. These analyses aim to predict students' comprehension and performance, thus contributing to identifying materials that best capture attention and facilitate learning in STEM topics.In another study [59], monitoring concentration and learning efficiency in interdisciplinary activities with modern technologies and mobile applications proved an effective approach to enhancing learning in areas such as ecological agriculture and environmental protection.

In the context of problem-solving, neurotechnologies enabled the exploration of aspects such as working memory, long-term memory, and visuospatial cognitive processes, which are fundamental for conceptualization and performance in convergent tasks[60]. Convergent tasks explored in the study are distinguished by offering specific and well-defined solutions, requiring logical reasoning, analytical skills, and the integration of mental representations.An example is calculating the dimensions of a screen using the Pythagorean theorem. Another case involves manipulating geometric shapes, where it is necessary to create and compare mental images to satisfy the given conditions. Additionally, hybrid tasks that combine simple mathematical calculations with scenario visualization demonstrate the importance of cognitive flexibility. In all these situations, effective performance depends on the ability to access previously stored knowledge and combine it with visual mental models. These examples highlight how convergent tasks contribute to the development of essential competencies in STEM education by integrating cognitive processes and practical strategies in problem-solving.

Additionally, monitoring cognitive load through EEG and eye tracking presents opportunities to enhance data collection and analysis methods, especially during the development of tasks aimed at understanding relationships between structure and function. These concepts, explored in the study, are essential in biology and chemistry as they explain how the organization or configuration of a component is directly related to its functional role or performance. This relationship was investigated through activities involving the manipulation of models and virtual environments, allowing students to deepen their understanding of how molecular structures influence biochemical processes while researchers used neurophysiological tools to monitor cognitive states during interactions [61].

Although the benefits of using neurotechnologies in STEM contexts are widely reported in these studies, it is crucial to consider the limitations of these works to interpret the results cautiously. Many analyzed studies feature small sample sizes, often limited to small groups of participants, which hinders the generalization of conclusions to larger populations. Additionally, the contexts in which these technologies were applied vary significantly, encompassing different educational levels, disciplines, and pedagogical approaches, making it challenging to generalize findings. These limitations highlight the need to expand research in the field with studies that employ more representative samples and include greater diversity in educational scenarios, allowing for a more robust and comprehensive evaluation of the impacts of these technologies. In the next section, we will examine the implications for educational development.

IV. Main Findings And Their Implications

A In this section, we present the findings related to the use of neurotechnologies in STEM educational contexts, corre-lating them with studies that have both practical and scien-tific implications. The areas addressed include the moni-toring of cognitive processes, the use of brain-computer interfaces as an educational tool, and the application of machine learning algorithms.

Monitoring Cognitive Processes in STEM

Tools such as EEG, fNIRS, and eye trackers, used inde-pendently or in combination, allow for the monitoring of cognitive processes and emotional states, including work-ing memory, attention, cognitive load, and engagement [41], [62], [63], [64], [65]. These methods provide bio-metric data analyses on different learning styles, helping educators better understand how students process infor-mation, enabling personalized adjustments to teaching strategies [16], [40].

Recent research has shown that neural alignment, or syn-chronization of neural activity between individuals, plays a relevant role in group learning. Studies in natural educa-tional environments, such as classrooms, indicate that the correlation between students' and teachers' brain activities can signal levels of engagement and content retention. Neurotechnologies have been used to monitor this syn-chronization during different teaching methods, revealing that higher brain alignment can aid in information retention [66]. Additionally, social factors [67], such as the per-ceived proximity between teacher and student, also influ-ence neural alignment, highlighting the importance of in-terpersonal dynamics in the educational process [46]. These findings reinforce the potential of brain alignment as an indicator of engagement and learning effectiveness, offering new perspectives for developing more effective pedagogical practices [49], [68].

We also observed that neurotechnologies have revealed specific neural connections between different brain lobes during activities when analyzed through mathematical models and software tools [69]. Similar to other studies in the educational field, the research reviewed in this study demonstrates that engagement in STEM tasks activates specific brain regions, providing a more detailed view of learning processes and enabling more targeted interven-tions [70], [71].

The analysis of these processes facilitates the tracking of metrics during learning, contributing to advancements in educational research. Integrating the data obtained with traditional cognitive measures expands the understanding of the educational experience [14], [15], [19], [40], [41], [53], [72].

BCI as an Educational Tool in STEM Contexts

Brain-computer interfaces (BCIs) have emerged as inno-vative educational tools, offering new possibilities for enhancing learning and understanding brain function. Us-ing brain signals captured by devices such as EEG, BCIs translate neural activity into commands that can be used for monitoring, neurofeedback, and interaction with digital systems[42], [73]. In education, these technologies have been applied to train cognitive functions such as concen-tration and memory, as well as to explore students' emo-tional states [74], allowing for a more personalized learn-ing experience. Examples include games that enhance fo-cus and brain health in an interactive way [75], [76].

Additionally, BCIs have the potential to assist students with specific difficulties, such as ADHD and ASD, provid-ing support tailored to their needs [77], [78]. By combining technological innovation and neuroscience, BCIs pave the way for a more inclusive and effective education.

Use of Machine Learning Algorithms in Brain Da-ta Analysis in STEM Contexts

The use of machine learning (ML) algorithms has enabled more in-depth analyses of brain activity during educational activities [79], allowing for the analysis of neural data to personalize the teaching process [80]. Machine learning algorithms, such as neural networks and classification methods, help decode complex brain signals and identify patterns related to cognitive load, situational interest, and students' emotional states [81], [82].

These data are used to create adaptive learning environ-ments, such as EEG- and eye tracker-based systems that adjust tasks according to students' mental workload, pro-moting optimal learning conditions [63], [83], [84], [85], [86]. Furthermore, this integration between AI and neuro-technologies not only enhances teaching efficiency but also expands educational inclusion by addressing the spe-cific needs of different student profiles.

V. Conclusions

This systematic review highlighted the main applications and benefits of neurotechnologies in STEM educational contexts, emphasizing the use of devices such as EEG, fNIRS, and eye trackers. Their contributions to monitoring cognitive processes, personalizing teaching, and developing evidence-based pedagogical strategies were explored. Additionally, advancements brought by brain-computer interfaces (BCIs) and the fundamental role of machine learning algorithms in decoding neural data and dynamicallyadjusting the learning process were addressed.

Despite these contributions, it is important to acknowledge the limitations of the analyzed studies, which hinder the formulation of generalizations. The small number of articles included in the systematic review represents a significant limitation, as it restricts the diversity of assessedscenarios and populations. Although the use of emerging neurotechnologies is expanding, their recent incorporation into the educational field still presents challenges, such as the need for technical knowledge to operate these tools, the application of rigorous protocols to obtain valid data, and the costs involved in acquiring or developing devices. These factors limit the number of studies in the educational field and lead many researchers to work with small samples, compromising the statistical robustness and applicability of the results. The heterogeneity of methods and technologies used, combined with the diversity of educational contexts, also makes it difficult to directly compare studies and draw universally applicable conclusions.

Another relevant aspect is the restriction in inclusion criteria, which limited the search to a specific period and certain databases. This choice was necessary to ensure the feasibility of the study, considering the rapid pace of technological evolution and the resources available. However, expanding these criteria in future reviews, covering longer periods and additional databases, could provide a broader and more detailed view of the field, increasing the reliability and relevance of the findings.Acknowledging these limitations, it is evident that more studies are needed to consolidate the use of neurotechnologies in STEM education. Future research should prioritize larger samples, greater methodological standardization, and the inclusion of contextual variables, as well as foster integration between different approaches and technologies. Even so, this study fulfilled its objective by laying the groundwork for the development of an adaptive system that uses physiological data acquired through neurotechnologies, identifying patterns of behavior and performance during educational activities.

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